Diversification in Lottery-Like Features and Portfolio Pricing Discounts*

Xin Liu[a]

[a] *School of Management, University of Bath*

First Draft: May 2017

This Version: November 2018

Abstract

Why do portfolios often trade at discounts relative to the sums of their components? I provide a novel explanation based on the prospect theory. I extend the model of Barberis and Huang (2008) and consider multiple assets which may or may not produce extreme positive payoffs together. My model predicts that when these assets do not produce extreme payoffs together, a portfolio consisting of them will trade at a discount relative to the market value when they are traded alone. I present three sets of empirical evidence to support this prediction and provide a novel and unifying explanation for the closed-end fund puzzle, the announcement returns of mergers and acquisitions, and conglomerate discounts.

Keywords: Cumulative Prospect Theory, *CoMax*, Diversification, Lottery-like Feature, Discount

JEL Classification: G11, G12, G41

---

* I would like to thank Tse-Chun Lin, Shiyang Huang, Chengxi Yin, Dong Lou, Kewei Hou, Augustin Landier, Dimitri Vayanos, Mike Adams, Alan Kwan, Fengfei Li, Andrew Sinclair, Hanwen Sun, Thomas Schmid, Chi-Yang Tsou, Mingzhu Tai, Hong Xiang, Ru Xie, Tong Zhou, Hong Zou, all seminar participants at China Economics Annual Conference 2018, China Finance Annual Meeting 2018, Financial Management Association Annual Meeting 2018, German Finance Association Annual Meeting 2018, Research in Behavioral Finance Conference 2018, Greater China Area Finance Conference 2018, American Finance Association Annual Meeting 2018 Ph.D. Poster Session, Financial Management Association Annual Meeting 2018 PhD Consortium, Guanghua Finance Doctoral Consortium 2017, University of International Business and Economics, Sun Yat-Sen University, Central University of Finance and Economics, Renmin University of China, Peking University HSBC Business School, University of Bath, University of East Anglia, University of Leicester, University of Nottingham, and The University of Hong Kong for helpful comments and suggestions. This paper was previously circulated under the title "Co-maxing out and Security Prices".

Xin Liu: X.Liu2@bath.ac.uk

Diversification in Lottery-Like Features and Portfolio Pricing Discounts

First Draft: May 2017

This Version: September 2018

Abstract

Why do portfolios often trade at discounts relative to the sums of their components? I provide a novel explanation based on the prospect theory. I extend the model of Barberis and Huang (2008) and consider multiple assets which may or may not produce extreme positive payoffs together. My model predicts that when these assets do not produce extreme payoffs together, a portfolio consisting of them will trade at a discount relative to the market value when they are traded alone. I present three sets of empirical evidence to support this prediction and provide a novel and unifying explanation for the closed-end fund puzzle, the announcement returns of mergers and acquisitions, and conglomerate discounts.

Keywords: Cumulative Prospect Theory, *CoMax*, Diversification, Lottery-like Feature, Discount

JEL Classification: G11, G12, G41

1 Introduction

In the financial market, a portfolio is sometimes valued less than the market value of its underlying components. For example, closed-end fund shares are typically traded at prices lower than the per share market value of its underlying assets (e.g., Lee, Shleifer and Thaler, 1991; Chen, Kan, and Miller, 1993; Pontiff, 1996; Hwang, 2011; Wu, Wermers, and Zechner, 2016; Hwang and Kim, 2017); mergers and acquisitions often have negative combined announcement returns from acquirers and targets (for example, Morck, Shleifer, and Vishny, 1990; Moeller, Schlingemann, and Stulz, 2005; Masulis, Wang, and Xie, 2007; Cai and Sevilir, 2012); conglomerates are usually worth less than a portfolio of comparable single-segment firms (e.g., Lang and Stulz, 1994; Berger and Ofek, 1995; Servaes, 1996; Lamont and Polk, 2001; Laeven and Levine, 2007; Hund, Monk, and Tice, 2010). These phenomena are puzzling because they violate the market efficiency hypothesis. In this paper, I provide a novel and unifying explanation for these puzzles based on the prospect theory.

Under the prospect theory framework of Tversky and Kahneman (1992), Barberis and Huang (2008) show that a lottery-like stock (i.e., a stock with an extremely positively skewed return distribution) can become overpriced because investors overweight the small probability of a large payoff. To analyze the aforementioned phenomena, I extend Barberis and Huang (2008) and consider multiple lottery-like stocks. These lottery-like stocks can provide extreme positive payoffs with a small probability, but they may or may not produce extreme payoffs at the same time. I solve and compare asset prices in two economies. In the first economy, investors can trade these lottery-like stocks freely. In the second economy, investors can only trade a portfolio consisting of these lottery-like stocks. I find that the portfolio price in the second economy is lower than the prices of these lottery-like stocks in the first economy (the difference is referred as the portfolio pricing discount here after). More importantly, the portfolio pricing discount depends on how likely these lottery-like stocks produce extreme payoffs together. Specifically, when the stocks are more likely to produce extreme payoffs together, the portfolio pricing discount is smaller.

The intuition behind this prediction is based on the prospect theory and the diversification in lottery-like features. If lottery-like stocks have a low tendency of producing extreme payoffs together, when they are combined into a portfolio (e.g., a closed-end fund), the return distribution of this portfolio will become a lot smoother than each individual stock due to diversification. In other words, the portfolio is less lottery-like. Under the prospect theory, this portfolio becomes relatively less attractive to investors and tends to be traded at a lower price. In contrast, when investors trade each individual lottery-like stock, the lottery-like feature makes the stock attractive and the stock tends to be traded at a higher price. Therefore, the portfolio is traded at a discount relative to the market prices of its underlying stocks. Meanwhile, if the underlying stocks always produce extreme payoffs together, when these stocks are combined into a portfolio, the portfolio obtains the same lottery-like feature. Thus, the portfolio is as attractive as each individual stock to investors and there is no portfolio pricing discount.

To test this theoretical prediction, I use closed-end funds (CEFs) as my main setting. I also find consistent results using mergers and acquisitions (M&As) and conglomerates. I use CEFs as the main setting for the following reasons. Firstly, a large body of literature has documented that a CEF share is typically traded at a lower price compared to the per share market value of its underlying assets. This discount has been a long-stand puzzle among academics and practitioners. Second, CEFs provide a clean setting to control firm-specific fundamental characteristics. Since stocks are combined and traded "as a package", the difference in value between a portfolio and the sum of its holdings should not be affected by firm-specific fundamentals characteristics, particularly those that are potentially correlated with lottery-like features.[1] Utilizing this advantage, my paper provides a relatively clean and powerful approach to test the relevance of the prospect theory and lottery-like features in determining asset prices, by directly comparing the market price of the portfolio with its intrinsic value (the market value of underlying stocks).

Empirically, the two key variables are: (1) the lottery-like payoff; and (2) the tendency that lottery-like payoffs are produced together. For the lottery-like payoff, I follow Bali, Cakici, and Whitelaw (2011) and use the average top-five daily returns within a month ($Max5$) to

[1] For example, Boyer, Mitton, and Vorkink (2010) use firm size (among others) to compute expected idiosyncratic skewness, making their measure mechanically correlated with size; Barberis, Mukherjee, and Wang (2016) report that their "prospect theory value" has a correlation of 36% with size and −34% with book-to-market ratio.

proxy for the degree of lottery likeness.[2] I denote CEF_Max5 as the $Max5$ for a CEF, and $Holding\_Max5$ as the average $Max5$ from a CEF's holdings, weighted by their holding percentage. The relative degree of lottery likeness, Ex_Max5, is defined as the difference between CEF_Max5 and $Holding\_Max5$.

To measure the tendency that stocks produce extreme payoffs together, I produce a measure called $CoMax$ based on the top-five daily returns within a month. Specifically, for every possible stock pairs within a CEF's holdings, I check the percentage of the top-five daily returns that are recorded in the same day, and denote it as $CoMax5$. By construction, $CoMax5 \in [0,1]$. The lottery likeness of each stock pair, $Pair\_Max5$, is the average $Max5$ of the two stocks, weighted by holding percentage. $Pair\_Max5 \times CoMax5$ provides useful information about both the degree of lottery likeness and the tendency of paying out "jackpots" together for each stock pair. These variables are further integrated at the fund level based on holding weights.

In my empirical tests, I focus on top-10 holdings from each CEF. The reasons are as follows. Firstly, the average CEF in my sample holds around a hundred stocks. It is impossible for investors to know the detailed holding list of each CEF. On the contrary, top10 holdings are readily observable from a fund's website, factsheets, and financial medias (such as Morningstar, Yahoo! Finance, etc.) for retail investors, who are the primary investors on CEFs.

---

[2] Similar results can be obtained using top 1/2/3/4 daily returns within a month as well. I use $Max5$ for the main results to allow for more variation when I construct the variable to capture the tendency that lottery-like payoffs are produced together.

Second, top-10 holdings account for a substantial portion of the total portfolio value and represent the investment objectives of the fund. That being said, including all holding stocks produces qualitatively similar results.

I find empirical results consistent with my theoretical predictions. First of all, I find that lottery-like features indeed get diversified at CEF level. When stocks are combined into a CEF, the lottery-like feature of the fund drops about 41%. Secondly, the difference in the lottery-like features between the CEF and its underly stocks can help explain the CEF discount. Specifically, a one-standard-deviation increase in the relative lottery likeness of a CEF's top-10 holdings (i.e., a one-standard-deviation drop in Ex_Max5) comes with 0.99% increase in the CEF discount (*t*-statistic = 2.81). Thirdly, the tendency of stocks producing extreme payoffs together, i.e., $CoMax5$, plays an important role in affecting the CEF discount. A one-standard-deviation increase in $Pair\_Max5 \times CoMax5$ can help offset the discount by 0.52% (*t*-statistic = 2.92). Results survive the inclusion of various variables known to be associated with CEF discounts. For reference, the average CEF discount in my sample is 4.70%. Therefore, these results are both statistically and economically significant.

Moreover, I extend my empirical tests to incorporate M&A deals and conglomerates. In a M&A deal, the new joint firm can be regarded as a "portfolio" which has two "underlying stocks": the acquirer and the target. The combined announcement-day return from both the acquirer and the target (denoted as $Combined\_CAR[-1,+1]$) can proxy for the difference between the value of the "portfolio" (the new joint firm) and the total value of its "underlying assets" (the acquirer and the target as two separate firms). As my final setting, a conglomerate can also be regarded as a "portfolio" of different business segments. Prior literature has shown that a conglomerate usually has a lower market-to-book ratio compared to its single-industry counterparts. Consistent with the CEF setting, I find that the diversification in lottery-like features can help explain the combined announcement-day return from the acquirer and the target and the low market-to-book ratio of conglomerates.

A potential concern from these three sets of results is that whether $CoMax$ simply captures return correlation. It is a fair challenge because $CoMax$ and return correlation are mechanically correlated. To show that it is indeed $CoMax$ that drives my results, I conduct placebo tests by replacing $CoMax$ with Non_Max_Corr, a return correlation constructed after excluding concurrent extreme returns. In all three settings, the results completely disappear.

Since the diversification in lottery-like features hampers a CEF's price, it is natural to wonder if fund managers are aware of this situation and have tried to avoid lottery-like stocks. I conduct additional tests based on propensity score matching to find out the answer. Specifically, for each of the top-10 holdings at fund inception, I collect ten pseudo stocks which are similar to the actual holding by reference to a host of firm characteristics but are not selected into the fund. I construct stock pairs from the actual top-10 holdings and the 100 pseudo holdings. Same as before, I compute $Pair\_Max5$, $CoMax5$, and $Pair\_Max5 \times CoMax5$ for each stock pair. Then, I conduct logit regressions with a dependent variable equals to one if the stock pair is from the actual top-10 holdings, and zero otherwise. I find that increasing $Pair\_Max5$ by one-standard-deviation lowers the likelihood of the two stocks being selected at fund inception by 19%. On the other hand, increasing $CoMax5$ by one-standard-deviation makes the two stocks 30% more likely to be selected at fund inception. Similar analyses from the M&A setting shows that firms with strong lottery-like features and high $CoMax$ are more likely to reach an M&A deal.

My paper has the following contribution to the literature. First of all, I extend Barberis and Huang (2008)'s model and consider multiple lottery-like stocks and the tendency that these stocks produce extreme payoffs together. I show that a portfolio consisting of these lottery-like stocks trade at a discount, and this discount depends on how likely these lottery-like stocks produce extreme payoffs together. Second, I utilize CEFs, M&As, and conglomerates to test this prediction and find consistent results. Finally, my findings not only support prospect theory from a new perspective, but also provide a novel and unifying framework for three seemingly unrelated phenomena, i.e., the closed-end fund puzzle, the combined announcement-day return of a M&A deal, and the conglomerate discount.

The rest of the paper is organized as follows: Section 2 describes my model and predictions. Section 3 explains data and main variables. Sections 4 presents my main results. Section 5 carries out further discussions on managerial implications. Section 6 concludes.

2 The Model

In Section 2.1, I revisit the original model setup from Barberis and Huang (2008) with two identical lottery-like stocks and solve the equilibrium price for these two stocks in this economy as a benchmark. In Section 2.2, I introduce a second economy, in which investors can not directly trade these lottery-like stocks, but can only trade a portfolio with equal-weights on these lottery-like stocks. I describe the equilibrium conditions for this portfolio. In Section 2.3, I provide some numerical results based on the same set of parameters adopted in Barberis and Huang (2008) and show how the portfolio discount is determined by the likelihood that these two lottery-like stocks produce extreme payoffs together ($CoMax$), given a fixed degree of lottery-like feature. In Section 2.4, I show how the portfolio discount varies with both $CoMax$ and the degree of lottery likeness.

2.1 Model Setup

Following Barberis and Huang (2008), a representative investor has the following value function:

$$v(x) = \begin{cases} x^{\alpha} & x \geq 0 \\ -\lambda(-x)^{\beta} & x < 0 \end{cases} . \tag{1}$$

For $\alpha \in (0,1)$, $\beta \in (0,1)$, and $\lambda > 1$, this value function is concave over gains, convex over losses, and exhibits a greater sensitivity to losses than to gains. λ, which is the coefficient of loss aversion, determines the degree of sensitivity to losses.

This representative investor applies probability weighting functions to the cumulative probability distribution of gains and losses, instead of the probability density function. This is a sharp distinction proposed by Tversky and Kahneman (1992) from their original prospect theory. Specifically, the functional forms are:

$$w^+(P) = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^{\frac{1}{\gamma}}} \ , w^-(P) = \frac{P^\delta}{(P^\delta + (1-P)^\delta)^{\frac{1}{\delta}}} \ , \tag{2}$$

where w^+ and w^- are the probability weighting functions for gains and losses, respectively. P is the cumulative probability distribution function. For $\gamma \in (0,1)$ and $\delta \in (0,1)$, the representative investor overweights small probabilities, i.e., for small and positive P, $w(P) > P$.

I consider a one-period economy with two dates, $t = 0$ and $t = 1$. The economy contains a risk-free asset, which is in perfectly elastic supply and has a gross return of r_f. There is a market portfolio and two skewed securities in this economy. The excess return on the market portfolio, excluding the skewed securities, is normally distributed:

$$r_m \sim N(\mu_m, \ \sigma_m^2). \tag{3}$$

Each of the skewed securities follows a binomial distribution: with a low probability v, the security pays out a large "jackpot" J, and with probability $1 - v$, it pays out nothing. For a very large J and a very small v, this binomial distribution resembles a lottery ticket. The returns on the skewed securities are independent of the market portfolio, and the payoffs from the skewed securities are infinitesimal relative to the total payoff from the market portfolio. In the equilibrium, these skewed securities should be priced equally. I denote this price as p_l, and the excess return of the skewed securities, $r_{l,i}$ $(i = 1 \text{ or } 2)$, is distributed as

$$r_{l,i} \sim \left(\frac{J}{p_l} - r_f, v;\ -r_f, 1 - v\right). \tag{4}$$

In this economy, Barberis and Huang (2008) propose an equilibrium with three global optima: a portfolio that combines the risk-free asset, the market portfolio, and a positive $\phi^* > 0$ in just the first (second) skewed security; and a portfolio that holds only the risk-free asset and the market portfolio. They demonstrate that this proposed equilibrium does exist with the following parameters: $(\alpha, \beta, \gamma, \delta, \lambda) = (0.88, 0.88, 0.65, 0.65, 2.25)$ and $(\sigma_m, r_f, J, v) = (0.15, 1.02, 10, 0.09)$. In the equilibrium, $(p_l, \phi^*) = (0.925, 0.085)$. This equilibrium price is the benchmark for the portfolio pricing in my second economy.

2.2 Portfolio Pricing

Now I consider a second economy. In this economy, the representative investor cannot directly trade the two skewed securities, but they can trade a portfolio which invests equally in the two skewed securities. The excess return of the portfolio depends on the probability that both skewed securities pay out "jackpots" at the same time. I denote

$$\Pr\left(\left(r_{l,1} = \frac{J}{p_l} - r_f\right) \cap \left(r_{l,2} = \frac{J}{p_l} - r_f\right)\right) = u\ . \tag{5}$$

Therefore,

$$\Pr\left(\left(r_{l,1} = \frac{J}{p_l} - r_f\right) \cap \left(r_{l,2} = -r_f\right)\right) = v - u\ , \tag{6}$$

$$\Pr\left((r_{l,1} = -r_f) \cap \left(r_{l,2} = \frac{J}{p_l} - r_f\right)\right) = v - u \ , \tag{7}$$

$$\Pr\left((r_{l,1} = -r_f) \cap (r_{l,2} = -r_f)\right) = 1 - 2v + u \ . \tag{8}$$

I define $CoMax$ as:

$$\begin{aligned} CoMax &= \frac{\Pr\left(\left(r_{l,1} = \frac{J}{p_l} - r_f\right) \cap \left(r_{l,2} = \frac{J}{p_l} - r_f\right)\right)}{\Pr\left(r_{l,1} = \frac{J}{p_l} - r_f\right)} \\ &= \frac{\Pr\left(\left(r_{l,1} = \frac{J}{p_l} - r_f\right) \cap \left(r_{l,2} = \frac{J}{p_l} - r_f\right)\right)}{\Pr\left(r_{l,2} = \frac{J}{p_l} - r_f\right)} \\ &= \frac{u}{v} \end{aligned} \tag{9}$$

The excess return of the portfolio, r_s , is distributed as:

$$r_s \sim \left(\frac{J}{p_s} - r_f, u;\ \frac{J}{2p_s} - r_f, 2v - 2u;\ -r_f, 1 - 2v + u\right) . \tag{10}$$

where p_s is the price of the portfolio.

I now search for the equilibrium price for this new portfolio. Two types of equilibrium may exist, depending on parameters. A homogeneous holdings equilibrium is an equilibrium in which all investors with access to the new portfolio hold the same position. In this equilibrium, each investor will hold an infinitesimal amount ε^* of the new portfolio. According to Barberis and Huang (2008), the expected excess return on this new portfolio should be zero, or more precisely, infinitesimally greater than zero.[3]

$$E(r_s) = u\left(\frac{J}{p_s} - r_f\right) + (2v - 2u)\left(\frac{J}{2p_s} - r_f\right) - (1 - 2v + u)r_f = 0 \ . \tag{11}$$

[3] See Proposition 2 in Barberis and Huang (2008)

$$p_s = \frac{vJ}{r_f} \ . \tag{12}$$

Note that in a homogeneous holdings equilibrium, the price of the portfolio, p_s, does not depend on u.

The other type of equilibrium is a heterogenous holdings equilibrium with two groups of investors, where all investors in the first group hold a combination of the risk-free asset, the market portfolio, and the new portfolio; and all investors in the second group hold the risk-free asset and the market portfolio but takes no position in the new portfolio. Markets are cleared by assigning each investor to one of the optima. According to Barberis and Huang (2008), a heterogeneous holdings equilibrium should satisfy the following conditions:

$$V(r_m) = V(r_m + \phi^* r_s) = 0 \ , \tag{13}$$

$$V(r_m + \phi r_s) < 0 \quad for \quad 0 < \phi \neq \phi^*, \tag{14}$$

$$V(r_s) < 0 \ , \tag{15}$$

where

$$V(r_m + \phi r_s) = -\int_{-\infty}^{0} w\left(P_\phi(r)\right) dv(r) + \int_{0}^{\infty} w\left(1 - P_\phi(r)\right) dv(r) \ \ , \tag{16}$$

and

$P_\phi(r) = \Pr(r_m + \phi r_s \leq r)$

$$= \Pr\left(r_s = \frac{J}{p_s} - r_f\right) \Pr\left(r_m \leq r - \phi\left(\frac{J}{p_s} - r_f\right)\right)$$

$$+ \Pr\left(r_s = \frac{J}{2p_s} - r_f\right) \Pr\left(r_m \leq r - \phi\left(\frac{J}{2p_s} - r_f\right)\right)$$

$$+ Pr(r_s = -r_f) \Pr(r_m \leq r + \phi r_f)$$

$$= uN\left(\frac{r - \phi\left(\frac{J}{p_s} - r_f\right) - \mu_m}{\sigma_m}\right) + 2(v-u)N\left(\frac{r - \phi\left(\frac{J}{2p_s} - r_f\right) - \mu_m}{\sigma_m}\right)$$

$$+(1 - 2v + u)N\left(\frac{r + \phi r_f - \mu_m}{\sigma_m}\right), \tag{17}$$

Here, ϕ^* is the fraction of wealth allocated to the new portfolio relative to the fraction allocated to the market portfolio for investors from the first group, and $N(.)$ is the cumulative normal distribution function. In a heterogeneous holdings equilibrium, the price of the new portfolio, p_s, depends on not only the skewness from its holdings (v), but also the probability that both skewed securities pay out “jackpots” at the same time $(CoMax)$.

2.3 An Example

Now I search for the equilibrium price of the new portfolio for each possible $CoMax$. To do this, I construct an explicit example under the same set of parameters adopted in Barberis and Huang (2008): $(\alpha, \beta, \gamma, \delta, \lambda) = (0.88, 0.88, 0.65, 0.65, 2.25)$ and $(\sigma_m, r_f, J, v) = (0.15, 1.02, 10, 0.09)$. I start by a special case: when $CoMax = 1$ (i.e., $u = v$), the portfolio is just another skewed asset identical to the two skewed securities in the economy. Therefore, the portfolio should be priced at 0.925, equals to the price of the two skewed securities from the first economy. At this price, the market with the new portfolio has a heterogenous holdings equilibrium in which the two global optima are $\phi = 0$ and $\phi = 0.085$. No discount should be observed.

As $CoMax$ goes down, the skewness of the portfolio drops while the expected payoff of the portfolio remains the same. As investors only value the tails of their wealth distribution, the portfolio becomes less attractive and should be traded at a lower price. For example, when $u = 0.08$, a heterogenous holdings equilibrium can exist. Specifically, I find that the price level $p_s = 0.922$ satisfies conditions (13) - (15). Figure 1a provides a graphical illustration. For this value of p_s, the red line plots the value function $V(r_m + \phi r_s)$ for a range of values of ϕ, where ϕ is the amount allocated to the skewed portfolio relative to the amount allocated to the market portfolio. The two global optima are obtained at $\phi = 0$ and $\phi = 0.088$. Market is cleared by assigning each investor to one of the two global optima. Compared to the price of each individual skewed security in the first economy, the portfolio is traded at a discount:

$$Discount = \frac{p_s - p_l}{p_l} = \frac{0.922 - 0.925}{0.925} = -0.32\% \ . \tag{18}$$

[Figure 1 Here]

The intuition of the heterogenous holdings equilibrium is as follows. When investors hold a small position in the new portfolio relative to their existing position in the market portfolio, their utility drops because the new portfolio has a negative expected return ($E(r_s) = vJ/p_s - r_f = -4.39\%$). As the position on the new portfolio increases, investors' wealth distribution starts to have a significant degree of skewness. This increases investors' utility because they overweights small probabilities and value skewness. At a price level of $p_s = 0.922$, the benefit of adding skewness to investors' wealth distribution offsets the negative excess return from holding the portfolio, producing both $\phi = 0$ and $\phi = 0.088$ as global optima.

For these parameter values, there exists no homogeneous holdings equilibrium, in other words, no equilibrium in which all investors with access to the new portfolio hold the same position. To see this is the case, according to (12), in a homogeneous holdings equilibrium,

$$p_s = \frac{vJ}{r_f} = \frac{0.09 \times 10}{1.02} = 0.882 \ . \tag{19}$$

For this value of p_s, the blue line in Figure 1a plots the value function $V(r_m + \phi r_s)$. The blue line clearly shows that $p_s = 0.882$ does not support an equilibrium, because all investors would prefer a substantial positive position in the portfolio to an infinitesimal one, making it impossible to clear the market.

However, when $CoMax$ is small, a homogeneous holdings equilibrium can be constructed but a heterogeneous holdings equilibrium cannot. In Figure 1b, the blue line shows that, when $u = 0.01$, $\phi = \varepsilon^* \to 0$ is not only a local optimum but also a global optimum. Therefore, all investors would prefer to hold an infinitesimal positive position, and the portfolio is traded at $p_s = 0.882$, or in other words, 4.65% discount.

The intuition for the homogenous holdings equilibrium is that, when $CoMax$ is small, the new portfolio is not sufficiently skewed. Therefore, no position, however large, can add enough skewness to investors' wealth distribution to compensate for the negative expected returns received from holding the portfolio. Since investors only overweight the right-tail of the distribution, cumulative prospect theory assigns the portfolio the same expected return that a concave expected utility theory would do, i.e., $E(r_s) = 0$.

With $u = 0.01$, a heterogeneous holdings equilibrium is not feasible. Specifically, $p_s = 0.818$ satisfies conditions (13). But the red line in Figure 1b shows that condition (14) is violated: the utility becomes positive for a small range of $\phi > 0$. Therefore, all investors would prefer a positive position in the new portfolio, making it impossible to clear the market.

For each value of $CoMax$, I search the price for the portfolio that satisfy a heterogenous holdings equilibrium first, and if it does not exist, the price for a homogeneous holdings equilibrium. I plot the relation between $CoMax$ and the portfolio discount in Figure 2.

[Figure 2 Here]

Figure 2 shows that, holding v constant, the model predicts a negative relation between $CoMax$ and the portfolio discount. When $CoMax = 1$, the portfolio is priced equally as the individual skewed securities. As $CoMax$ goes down, the skewness of the portfolio declines even though the expected payoff remains the same. This negatively affects the price of the portfolio because investors only overweight the right tails of their wealth distribution, making the portfolio trade at a discount relative to each individual skewed security. As $CoMax$ drops below 0.40, the portfolio cannot offer enough skewness to support a heterogeneous holdings equilibrium, and cumulative prospect theory assigns a price $p_s < p_l$ regardless of $CoMax$.

2.4 v, $CoMax$, and Portfolio Discount

In this section, I allow both v and $CoMax$ to vary and check how the portfolio discount is determined by both the "jackpot" probability and the tendency of paying off "jackpots" at the same time.

Similar patterns from Section 2.3 can be obtained for other low values of v as well. In Figure 3a, I plot the portfolio discount as a function of $CoMax$ for $v = 0.09$ (red line), $v = 0.07$ (blue line), and $v = 0.05$ (green line). In all three cases, a low $CoMax$ leads to a high portfolio discount. Provided the same level of $CoMax$, the discount on the portfolio is more sever when v is low, i.e., when the portfolio holds securities with a high degree of skewness. On the other hand, when v is high, the negative effect of $CoMax$ on the portfolio price is smaller. An extreme case is that when v is high enough (no lottery-like feature) so that only a homogenous holdings equilibrium exists, the portfolio price does not depend on $CoMax$ at all.

[Figure 3 Here]

In Figure 3b, I plot the portfolio discount as a function of v for $CoMax = 1.0$ (red line), $CoMax = 0.7$ (blue line), $CoMax = 0.4$ (green line), and $CoMax = 0.1$ (purple line). When $CoMax = 1.0$ (no diversification), the portfolio is always traded at a price equals to the skewed securities regardless of v. In the other three cases, a low v leads to a high portfolio discount. Provided the same level of v, the discount on the portfolio is more sever when $CoMax$ is small, i.e., when the two skewed securities do not tend to pay off "jackpots" at the same time. On the other hand, if the two skewed securities have high $CoMax$, the discount can be partially mitigated.

Therefore, the model predicts an interaction effect: a portfolio pricing discount appears when the portfolio holds securities with a high degree of skewness (low v) but do not tend to pay off "jackpots" together (high $CoMax$).

3 Data and Variables

In this section, I introduce samples and variables to test my model prediction: CEFs (Section 3.1), M&A (Section 3.2), and conglomerates (Section 3.3).

3.1 Closed-end Funds

The first set of empirical tests focuses on US equity closed-end funds.[4] A CEF is a type of publicly traded mutual fund which invests in other publicly traded securities. The nature that a CEF itself is traded in a stock exchange makes it possible to compare the market value of the fund with the total market value of its underlying assets.

Following the literature, I first extract a list of CEFs and their monthly prices from CRSP by selecting securities with share codes 14 and 44. The net asset value (NAV), i.e., the market value of a fund's underlying assets on a per-share basis, can be accessed from Compustat. The

[4] A CEF is defined as a US equity CEF if at least 50% of its weight is invested in stocks listed in US stock exchanges.

dependent variable is the CEF discount, which is defined as the difference between the price of a CEF and its NAV, divided by NAV:

$$Discount_{i,t} = \frac{Price_{i,t} - NAV_{i,t}}{NAV_{i,t}} \; . \tag{22}$$

For example, a CEF traded at \$4.9 but with a NAV of \$5 is described to have a premium of −2%. In other words, the CEF is traded at 2% discount. To avoid unnecessary confusion, I always describe results in terms of discounts, following the common convention and the fact that the majority of CEFs trade at discounts. To avoid distortions on the CEF discount after the initial public offering and shortly before a closed-end fund gets liquidated or becomes open-ending, I follow Chan, Jain, and Xia (2008) to exclude data within the first six months after a fund's IPO and in the month preceding the announcement of liquidation or open-ending.[5] I obtain CEFs' holdings from Morningstar. They are merged to CRSP by name and CUSIP.

The degree of lottery likeness is proxied by the average top-five daily returns within a month ($Max5$), following Bali, Cakici, and Whitelaw (2011). Similar results can be obtained using top 1/2/3/4 daily returns within a month as well. I use $Max5$ for the main results to allow for more variation in $CoMax$. I denote CEF_Max5 as the $Max5$ for a CEF, and $Holding\_Max5$ as the average $Max5$ from a CEF's holdings, weighted by holding percentage. Because both the holdings and the CEF itself can exhibit lottery-like features, I examine the relative degree of lottery likeness, Ex_Max5, which is define as:

[5] This exclusion does not affect my results.

$$Ex\_Max5 = CEF\_Max5 - Holding\_Max5. \tag{23}$$

I produce a measure for $CoMax$ based on the top-five daily returns within a month. Specifically, for every possible stock pairs within a CEF's holdings, I check the percentage of the top-five daily returns that are recorded in the same day, and denote it as $CoMax5$. For example, if the top-five daily returns for Stock A come from the 1st, 4th, 9th, 11th and 15th day of the month, while the top-five daily returns for stock B come from the 2nd, 4th, 9th, 14th and 20th day of the month, then $CoMax5$ equals 40% for this stock pair. By construction, $CoMax5 \in [0,1]$. For each pair of stocks, the average lottery likeness, $Pair\_Max5$, is the average $Max5$ of the two stocks, weighted by their respective holding percentages. $Pair\_Max5 \times CoMax5$ provides useful information about both the degree of lottery likeness and the tendency of paying out extreme returns together for each stock pair. $Pair\_Max5 \times CoMax5$, $Pair\_Max5$ and $CoMax5$ are further taken average across all possible stock pairs, weighted by the total holding percentage of each stock pair. I use the same notations for these aggregated variables. Note that after $Pair\_Max5$ is taken the weighted average across all stock pairs, it equals $Holding\_Max5$.

In my empirical tests, I focus on top-10 holdings from each CEF. The reasons are as follows. Firstly, the average CEF in my sample holds around a hundred stocks. It is impossible for investors to know the detailed holding list of each CEF. On the contrary, top10 holdings are readily observable from a fund's website, factsheets, and financial medias (such as Morningstar, Yahoo! Finance, etc.) for retail investors, who are the primary investors on CEFs.

Second, top-10 holdings account for a substantial portion of the total portfolio value and represent the investment objectives of the fund. That being said, including all holding stocks produces qualitatively similar results.

I consider the following control variables: disagreement, inverse price, dividend yield, expense ratio, liquidity ratio, excess skewness, and excess idiosyncratic volatility. Detailed descriptions of these variables can be found in the Appendix. My final sample contains 101 CEFs from 2002 to 2014. The sample period is determined by the availability of Morningstar.

Panel A of Table 1 reports summary statistics for the CEF sample. The average CEF discount is 4.7% with a standard deviation of 14.3%. The mean and standard deviation of the CEF discount is in line with those reported in prior studies (for example, Lee, Shleifer and Thaler, 1991; Chen, Kan, and Miller, 1993; Bodurtha, Kim, and Lee, 1995; Pontiff, 1996; Klibanoff, Lamont, and Wizman, 1998; Chan, Jain, and Xia, 2008; Hwang, 2011; Wu, Wermers, and Zechner, 2016; Hwang and Kim, 2017).

[Table 1 Here]

In Panel A of Table 2, I compare the lottery-like feature between a CEF and its holdings. The average $Max5$ for a CEF is 0.9% lower than the average $Max5$ for its holdings (*t*-statistic = −34.44). In other words, the average lottery-like feature of underlying stocks drops about 41% in magnitude when they are combined and traded as a portfolio. This shows that lottery-like features indeed get diversified away at the fund level.

[Table 2 Here]

3.2 Mergers and Acquisitions

The second set of empirical tests focuses on M&A. I extract details on M&A deals from the Securities Data Corporation's U.S. M&A database. Following Masulis, Wang, and Xie (2007), I require that: (1) the status of the deal must be completed; (2) the acquirer controls less than 50% of the target shares prior to the announcement; (3) the acquirer owns 100% of the target shares after the transaction; (4) the deal value disclosed in the SDC dataset is more than 1 million USD.

I obtain stock returns and accounting variables from CRSP and Compustat, respectively. These two datasets are merged with the SDC data based on name and CUSIP. The dependent variable is the combined announcement return, defined as the average cumulative abnormal return over days $[-1,+1]$ across the acquirer and the target, weighted by their market capitalizations in the month prior to the announcement:

$$Combined\_CAR[-1,+1] = w_A \times CAR_A[-1,+1] + w_T \times CAR_T[-1,+1], \tag{20}$$

where $t = 0$ is the announcement day, or the ensuing trading day if the deal is announced when the market is closed. $CAR_A[-1,+1]$ and $CAR_T[-1,+1]$ are cumulative abnormal returns over days $[-1,+1]$ for the acquirer and the target, respectively; w_A and w_T are weights based on market capitalizations for the acquirer and the target. I use DGTW-adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 1997) to compute $CAR_A[-1,+1]$ and

$CAR_T[-1,+1]$. $Combined\_CAR[-1,+1]$ captures the difference between the value of the joint firm (i.e., the "portfolio") and the total value of the acquirer and the target operating separately (i.e., the "underlying assets").

The degree of lottery likeness of the acquirer (target) is proxied by the average of the acquirer's (target's) top-3 monthly returns within the past year before the announcement ($Max3$).[6] This empirical strategy is in the same sprit as Bali, Cakici, and Whitelaw (2011). I use monthly returns over a year's horizon because investors evaluate M&A deals in a long horizon.[7] Yet I still use top $1/4$ of the data to identify extreme payoffs. $Combined\_Max3$, which captures the average degree of lottery likeness from a M&A deal, is the average lottery likeness from the acquirer ($Max3_A$) and the target ($Max3_T$), weighted by their respective market capitalizations (w_A and w_T) in the month prior to the announcement:

$$Combined\_Max3 = w_A \times Max3_A + w_T \times Max3_T. \tag{21}$$

To capture the likelihood that both the acquirer and the target pay out extreme returns at the same time, I define $CoMax3$ as the percentage of the top-3 monthly returns that are recorded in the same month. For example, if the top-3 monthly returns for Stock A come from month −10, −5 and −2, while the top-3 monthly returns for Stock B come from month −9, −5

---

6 Some existing studies also utilize monthly returns to capture the skewness of a return distribution, for instance, Mitton and Vorkink (2007), Barberis, Mukherjee, and Wang (2016).

7 Similar results can be obtained using weekly or daily returns.

and −3 (the month that the deal is announced is month 0), then $CoMax3$ equals 33% for this deal. By construction, $CoMax3 \in [0,1]$.

I consider the following control variables for both acquirers and targets: market capitalization, market-to-book ratio, return on assets, leverage, and operating cash flows. I consider the following control variables from deals: disagreement, relative size, tender offer, hostile offer, competing offer, cash only, stock only, same industry, combined skewness, and combined idiosyncratic volatility. Detailed descriptions of these variables can be found in the Appendix.

My final sample contains 1,145 M&A deals from 1989 to 2014. Summary statistics are reported in Panel B of Table 1. The average $Combined\_Max3$ is 1.6% with a standard deviation of 7.0%. I compare the lottery-like feature of acquirers and targets in Panel B of Table 2. On average, $Max3_T$ is 4.2% higher than $Max3_A$ (*t*-statistic = 11.63).

3.3 Conglomerates

The last set of tests focuses on conglomerates. A conglomerate is a firm operating in multiple industry segments. My data on firm segments is from Compustat, in which each segment is assigned a four-digit SIC code. I define a conglomerate as a firm operating across at least two different segments; I define a single-segment firm as a firm operating in only one segment. Following the standard literature (Berger and Ofek, 1995; Lamont and Polk, 2001; Mitton and Vorkink, 2010), I discard firm-year observations if Compustat assigns any segment a 1-digit SIC code of 0 (Agriculture, Forestry and Fishing), 6 (Finance, Insurance and Real

Estate), or 9 (Public Administration & Non-classifiable). I also drop firm-year observations that meet any of the following conditions: (1) total sales or total assets or book value of equity of the firm is missing or non-positive; (2) net sales from any of the segments is missing or non-positive; (3) the sum of sales from all segments is not within one percent of the total sales of the firm; and (4) total sales of the firm is less than 20 million USD.

After screening out defective observations, I match the rest of the data to CRSP. More specifically, I match book value from fiscal year $t-1$ to market value from June of calendar year t, and compute market-to-book ratios for both conglomerates and single-segment firms. The market-to-book ratio for a segment (Seg_MEBE) is defined as the sales-weighted average market-to-book ratios across all single-segment firms within the segment. The imputed market-to-book ratio ($Imputed\_MEBE$) is defined as the average Seg_MEBE across a conglomerate's segments, weighted by this conglomerate's net sales from each segment. The conglomerate discount is defined as the difference between a conglomerate's market-to-book ratio ($MEBE$) and its $Imputed\_MEBE$, scaled by $Imputed\_MEBE$:

$$Discount_{i,t} = \frac{MEBE_{i,t} - Imputed\_MEBE_{i,t}}{Imputed\_MEBE_{i,t}} \ . \tag{24}$$

I winsorize this variable at the 1st and 99th percentiles. To avoid unnecessary confusion, I always describe the results in terms of discounts, following the common convention and the fact that the majority of conglomerates trade at discounts. This variable captures the difference between the market value of a conglomerate (i.e., the "portfolio") and the overall market value of the segments related to this conglomerate (i.e., the "underlying assets").

Same as the M&A setting, the lottery-like feature for a firm is proxied by the average top-3 monthly returns within the fiscal year ($Max3$). To proxy for the lottery likeness of a segment, I conjecture that, when investors evaluate the lottery-like feature of a segment, they focus on the ones similar to the conglomerate. Therefore, five single-segment firms are selected from each segment based on the closeness of SIC code first and then net sales.[8] The lottery-likeness for each segment (Seg_Max3) is then defined as the sales-weighted average $Max3$ across these five single-segment firms. $Imputed\_Max3$ is defined as the average Seg_Max3 across a conglomerate's segments, weighted by this conglomerate's net sales from each segment. The relative lottery-likeness is defined as the difference between a conglomerate's $Max3$ ($Cong\_Max3$) and its $Imputed\_Max3$:

$$Ex\_Max3 = Cong\_Max3 - Imputed\_Max3 \ . \tag{25}$$

Trying to capture the tendency of two segments paying out extreme returns together is difficult. To the best of my knowledge, the previous literature provides little guidance on this attempt.[9] To have a similar proxy as the ones adopted in the previous two settings, I construct a $CoMax3$ measure for all possible stock pairs from any two different segments. For example, consider a conglomerate which operates in three segments, A, B, and C. This conglomerate has three segment pairs: (A, B), (A, C), and (B, C). Given segment pair (A, B), I choose one of the

[8] If fewer than 5 single-segment firms match at the 4-digit SIC level, I proceed to the 3-digit SIC level, and to the 2-digit SIC level if necessary, until at least 5 single-segment matches are found. If less than 5 matches are found at the 2-digit SIC level, the observation is excluded.

[9] The most obvious choice, which is using value-weighted average returns from each segment, does not serve the purpose here. Aggregating returns at segment level diversifies away lottery-like features.

five single-segment firms from Segment A, and one of the five single-segment firms from Segment B. This exercise leaves me 25 (5×5) stock pairs. I count the percentage of top-3 monthly returns that are recorded in the same month for each stock pair, and I take sales-weighted average across 25 pairs (Seg_CoMax) as a proxy for $CoMax$ between Segment A and Segment B. I repeat the exercise for the other two segment pairs. Finally, I take the average Seg_CoMax of these three segment pairs, weighted by this conglomerate's net sales from each segment pairs. $Pair\_Max3$ (sales-weighted average $Max3$ from the two stocks in the pair) and $Pair\_Max3 \times CoMax3$ are constructed in the same procedure. Note that, after taken weighted average across stock pairs and segment pairs, $Pair\_Max3$ becomes $Imputed\_Max3$. This method is enlightened by Green and Hwang (2012), who pool returns from all stocks in each of the FF-30 industries to compute that industry's skewness. My method is similar in spirit, as I pool a collection of individual stock returns to capture lottery-like features and $CoMax$ for segments.

Control variables for this setting include: disagreement, total assets, leverage, profitability, investment ratio, excess skewness, and idiosyncratic volatility. Detailed descriptions of these variables can be found in the Appendix.

As reported in Panel C of Table 1, my final sample contains 15,907 firm-year observations from 1977 to 2014. The average conglomerate discount in my sample is 13.0%, which is in line with the figures reported in prior literature (Berger and Ofek, 1995; Lamont and Polk, 2001, Mitton and Vorkink, 2010). Panel C of Table 2 compares lottery-like features between conglomerates and single-segment firms. The average $Max3$ from a conglomerate is 1.9% lower than the average $Max3$ from its comparable single-segment firms (*t*-statistic = −32.08).

4 Main Results

In this section, I document three sets of empirical evidence supporting my model prediction in Section 2: CEFs (Section 4.1), M&A (Section 4.2), and conglomerates (Section 4.3). I conduct placebo tests in Section 4.4 to show that my results are indeed driven by $CoMax$.

4.1 Closed-end Funds

My first set of tests focuses on CEFs. I estimate pooled OLS regressions with fixed effects and with standard errors clustered along both fund and time dimensions. The dependent variable is the CEF discount (in percentage). It captures the difference between the market value of the fund and the market value of its holdings. The independent variables of interests are Ex_Max5 and $Pair\_Max5 \times CoMax5$.

Control variables include disagreement, inverse CEF price, dividend yield, liquidity ratio, expense ratio, excess skewness, and excess idiosyncratic volatility. Detailed descriptions of control variables can be found in the Appendix. Hwang (2011) argues that inverse price and dividend yield have differential predictions on the CEF discount depending on whether the fund trades at a discount or at a premium. Therefore, I follow his paper and separate inverse price into two variables: $Inverse\ Price[pos]$, which equals to the inverse price if the fund trades at a premium, and zero otherwise; and $Inverse\ Price[neg]$, which equals to the inverse price if the fund trades at a discount and zero otherwise. $Dividend\ Yield[pos]$ and $Dividend\ Yield[neg]$ are defined in a similar fashion. All independent variables are standardized to have a mean zero and a standard deviation of one. The results are reported in Table 3.

[Table 3 Here]

I first test the relation between Ex_Max5 and the CEF discount. Since diversification is inevitable ($CoMax < 1$) in reality when selecting stocks into a CEF, my model predicts that a low Ex_Max5 (i.e., strong lottery-like feature from a CEF's holdings relative to the CEF itself) is associated with a high CEF discount.

The first three columns in Table 3 confirm this prediction. For example, in Column 3, after controlling for other variables related to the CEF discount, fund and time fixed effects, a one-standard-deviation decrease in Ex_Max5 is associated with 1.0% increase in the CEF discount (t-statistic = 2.81). For reference, the median CEF discount in my sample is 9.0%. Therefore, the effect on Ex_Max5 is both statistically and economically strong.

Next, I include $CoMax5$ and $Pair\_Max5 \times CoMax5$ into the analysis. As described in Section 3.1, for every possible stock pairs within a CEF's top-10 holdings, $CoMax5$ captures the percentage of the top 5 daily returns that are recorded in the same day for a stock pair, and $Pair\_Max5$ captures the average degree of lottery likeness from a stock pair. Thus, $Pair\_Max5 \times CoMax5$ provides useful information on both the degree of lottery likeness and the tendency that a CEF's holdings pay out extreme returns together. Then I take average $Pair\_Max5 \times CoMax5$, $CoMax5$, and $Pair\_Max5$ across all stock pairs in a CEF, weighted by the total holding percentages of stock pairs. After taken weighted average, $Pair\_Max5$ becomes $Holding\_Max5$. Therefore, I split Ex_Max5 into $Holding\_Max5$ and CEF_Max5 in these regressions. My model predicts a positive relation between $Pair\_Max5 \times CoMax5$ and the CEF discount.

Columns 5-7 confirm my results. Column 7 shows that a one-standard-deviation increase in $Pair\_Max5 \times CoMax5$ can offset the diversification effect by 0.5% (*t*-statistic = 2.92).

4.2 M&A

I make analogous observations for M&A deals. I estimate a pooled OLS regression with time-fixed effects and with standard errors clustered by time across 1,145 M&A events that meet data requirements. The dependent variable is the combined announcement-day return ($Combined\_CAR\ [-1,+1]$) (in percentage), where $t = 0$ is the announcement day, or the ensuing trading day if the deal is announced when the market is closed. It captures the difference between the market value of the joint firm (i.e., the "portfolio") and the total market value of the acquirer and the target operating separately (i.e., the "underlying assets"). The independent variables of interests are $Combined\_Max3$ and $Combined\_Max3 \times CoMax3$. I control characteristics from acquirers, targets and deals. Detailed description for all control variables can be found in the Appendix. All variables are standardized to have a mean of zero and a standard deviation of one. Results are reported in Table 4.

[Table 4 Here]

Table 4 shows that $Combined\_Max3$ negatively predicts $Combined\_CAR\ [-1,+1]$. In Column 2, a one-standard-deviation increase in $Combined\_Max3$ comes with 1.3% decrease on $Combined\_CAR\ [-1,+1]$ (t-statistic=−2.24). In my sample, the median $Combined\_CAR\ [-1,+1]$ is about 1.0%, therefore this effect is both statistically significant and economically large. This result is consistent with my model prediction. Since diversification is inevitable ($CoMax < 1$) in reality when conducting a M&A deal, strong $Combined\_Max3$ should negatively affect $Combined\_CAR\ [-1,+1]$ unconditionally.

Next, I include $CoMax3$ and $Combined\_Max3 \times CoMax3$ into the analysis. As described in Section 3.2, $CoMax3$ captures the percentage of the top-3 monthly returns that are recorded in the same month. Thus, $Combined\_Max3 \times CoMax3$ provides useful information on both the degree of lottery likeness and the tendency that both the acquirer and the target pay out extreme returns together. My model predicts a positive relation between $Combined\_Max3 \times CoMax3$ and $Combined\_CAR\ [-1,+1]$.

This prediction is confirmed in Columns 3 & 4. In Column 4, a one-standard-deviation increase in $Combined\_Max3 \times CoMax3$ can help offset the diversification effect by 0.7% (t-statistic = 4.00).

4.3 Conglomerate Firms

As an additional test, I check whether my model can help explain the conglomerate discount. Similar to the other two settings, I estimate pooled OLS regressions with time fixed effects and standard errors clustered by firm and time. The dependent variable is the conglomerate discount (not in percentage this time). This variable captures the difference between the market value of a conglomerate (i.e., the "portfolio") and the average market value of the segments associated with the conglomerate's business (i.e., the "underlying assets"). The independent variables of interests are Ex_Max3 and $Pair\_Max3 \times CoMax3$.

Control variables include: disagreement, log total assets, the square of log total assets, leverage, profitability, investment ratio, excess skewness, and excess idiosyncratic volatility. Detailed descriptions of control variables can be found in the Appendix. All independent variables are standardized to have a mean of zero and a standard deviation of one. Regression results are reported in Table 5.

[Table 5 Here]

I first test the relation between Ex_Max3 and the conglomerate discount. Since diversification is inevitable in reality ($CoMax < 1$) when a conglomerate expands into multiple segments, my model predicts that a low Ex_Max3 (i.e., strong lottery-like segments relative to the conglomerate itself) is associated with a high conglomerate discount.

The first two columns in Table 5 confirm this prediction. In Column 2, after controlling for other variables related to conglomerate discount and time fixed effects, a one-standard-deviation decrease in Ex_Max3 is associated with 19.5% increase in the conglomerate discount (t-statistic = 7.50). For reference, the median conglomerate discount in my sample is 29.2%. Therefore, the effect on Ex_Max3 is both statistically and economically strong.

Next, I include $CoMax3$ and $Pair\_Max3 \times CoMax3$ into the analysis. As described in Section 3.3, $CoMax3$ captures the percentage of the top-3 monthly returns that are recorded in the same month for a pair of stocks from two different segments, and $Pair\_Max3$ captures the average degree of lottery likeness from the stock pair. Thus, $Pair\_Max3 \times CoMax3$ provides useful information on both the degree of lottery likeness and the tendency that these two stocks pay out extreme returns together. I take weighted average for $Pair\_Max3 \times CoMax3$, $CoMax3$, and $Pair\_Max3$ across all stock pairs and segment pairs to produce a measure for the conglomerate. After taken weighted average across stock pairs and segment pairs, $Pair\_Max3$ becomes $Imputed\_Max3$. Therefore, I split Ex_Max3 into $Imputed\_Max3$ and $Cong\_Max3$ in these regressions. My model predicts a positive relation between $Pair\_Max3 \times CoMax3$ and the conglomerate discount.

Columns 3-5 confirm my results. Column 5 shows that, a one-standard-deviation increase in $Pair\_Max3 \times CoMax3$ can offset the diversification effect by 7.4% (t-statistic = 3.08).

4.4 Placebo Tests

A potential concern for the results documented in Sections 4.1-4.3 is that whether $CoMax$ simply captures return correlation. It is a fair challenge because $CoMax$ and return correlation are mechanically correlated. To address this concern, I conduct three placebo tests (one for each setting), replacing $CoMax$ with return correlation constructed after excluding the extreme returns that are recorded at the same time.

Take the CEF setting as an example. For each stock pair from a CEF's top-10 holdings, I retrieve the daily return series for both stocks during the month, and exclude any of the top 5 returns that are recorded in the same day. For example, if the top 5 daily returns for Stock A come from the 1st, 4th, 9th, 11th, and 15th day of the month, while the top 5 daily returns for stock B come from the 2nd, 4th, 9th, 14th, and 20th day of the month, then daily returns for Stock A and B on the 4th & 9th day of the month are excluded. Then, I calculate the return correlation between the two stocks using the rest of the daily returns and denote this correlation as Non_Max_Corr. I compute Non_Max_Corr and $Pair\_Max5 \times Non\_Max\_Corr$ for all possible top-ten stock pairs and take weighted average for a CEF. I replace Non_Max_Corr with $CoMax5$, replace $Pair\_Max5 \times CoMax5$ with $Pair\_Max5 \times Non\_Max\_Corr$, and reconduct the regressions in Columns 5-7 of Table 3. I report these results in Panel A of Table 6. The interaction term $Pair\_Max5 \times Non\_Max\_Corr$ becomes insignificant in all three columns.

[Table 6 Here]

For the M&A sample, I first retrieve the monthly return series from the past year for both the acquire and the target, and then exclude any of the top-3 monthly returns that are recorded in the same month. For example, if the top-3 monthly returns for Stock A come from month -10, month -5, and month -2 (the month that the deal is announced is month 0), while the top-

3 monthly returns for Stock B come from month −9, month −5, and month −3, then the monthly returns for Stock A and B on month −5 are excluded. I calculate the return correlation between the acquirer and the target using the rest of the monthly returns, and denote this correlation as Non_Max_Corr. I replace Non_Max_Corr with $CoMax3$, replace $Combined\_Max3 \times CoMax3$ with $Combined\_Max3 \times Non\_Max\_Corr$, and reconduct the regressions in Columns 3&4 of Table 4. I report these results in Panel B of Table 6. The interaction term $Combined\_Max3 \times Non\_Max\_Corr$ becomes insignificant in both columns.

Finally, I exploit the setting of conglomerates. For each of the two stocks from two different segments, I retrieve the monthly return series within the fiscal year for both stocks and exclude any of the top-3 monthly returns that are recorded in the same month. I calculate the return correlation between the two stocks using the rest of the monthly returns, and denote this correlation as Non_Max_Corr. I compute Non_Max_Corr and $Pair\_Max3 \times Non\_Max\_Corr$ for every two stocks from two different segments, and take weighted average across all stock pairs and segment pairs, as described before. I replace $CoMax3$ with Non_Max_Corr, replace $Pair\_Max3 \times CoMax3$ with $Pair\_Max3 \times Non\_Max\_Corr$, and reconduct the regressions in Columns 4&5 of Table 5. I report these results in Panel C of Table 6. The results previously documented in Table 5 disappear.

These three tests all show that return correlations during non-$CoMax$ period cannot explain CEF discounts, M&A announcement returns, or conglomerate discounts, and $CoMax$ is the real driving force for the results documented in Sections 4.1-4.3.

5 Further Discussion

Since the diversification in lottery-like features can have a negative effect on CEF prices and M&A announcement returns, it is natural to consider if managers are aware of this situation and have managed to mitigate the effects. This section tries to shed some lights on these two questions.[10]

5.1 Likelihood of Selection at CEF Inception

If fund managers are aware that the diversification in lottery-like features have a negative effect on CEF prices, they should avoid selecting stocks with strong lottery-like features. To test this conjecture, I check CEF holdings at fund inception.[11] For each of the top-10 stocks at inception, I identify 10 pseudo stocks that are not selected but are very similar to the actual holding. Specifically, I apply propensity score matching based on firm size, book-to-market ratio and past twelve months' return and select the 10 pseudo stocks that are closest to the actual holding in terms of propensity scores. I end up with 45 actual top-10 stock pairs and 4,500 pseudo pairs for each fund at inception. I estimate pooled logit regressions, where the dependent variable equals one if the stock pair consists of actual top-10 holdings, and zero otherwise. The independent variables of interests include $Pair\_Max5$, $CoMax5$, and

[10] Due to data limitations, I cannot conduct this exercise on conglomerates.

[11] Since holdings at the moment of IPO is not available, I take the first holding report shortly after a fund's inception as its holding position at inception. This should not be a big issue because a CEF's holdings are generally very persistent over time.

$Pair\_Max5 \times CoMax5$. I control for the average market capitalization, the average book-to-market ratio, and the average past twelve months' return for each stock pair. Results are reported in Panel A of Table 7.

[Table 7 Here]

Column 1 from Panel A of Table 7 shows that CEF managers tend to avoid stock pairs with strong lottery-like features.[12] The estimate on $Pair\_Max5$ is −0.239 (z-statistic = −6.83). This indicates that increasing $Pair\_Max5$ by one-standard deviation lowers the likelihood of the pair being included at the inception by 18.6% relative to the unconditional likelihood.[13]

Column 2 includes $CoMax5$ and $Pair\_Max5 \times CoMax5$ in the regression. The estimate on $CoMax5$ is −0.249 (z-statistic = −3.83). This indicates that increasing $CoMax5$ by one-standard deviation makes the pair 30.0% more likely to be included at the inception relative to the unconditional likelihood. The interaction term is not significant, which is not surprising considering that CEF managers tend to avoid strong lottery-like stocks.

5.2 Likelihood of M&A Deals

Similar exercises can be conducted in the M&A setting as well. If firm managers are aware that the diversification in lottery-like features have a negative effect on M&A announcement

---

12 Similar results can also be obtained if the regression is conducted at stock level instead of pair level.

13 This unconditional likelihood is $45/(45 \times 10 \times 10 + 45) = 0.0099$.

returns, acquirers (targets) with a strong lottery-like feature should merge with targets (acquirers) which have a strong lottery-like feature and also a high $CoMax$.

I conduct three tests based on propensity score matching to explore this prediction. In Columns 1 and 2 of Panel B Table 7, I match each acquirer with ten pseudo targets that are not involved in the M&A deal with this acquirer. Pseudo targets are determined through propensity score matching with reference to the same set of target characteristics and relative size to the acquirer as outlined in the Section 3.1. These pseudo targets are the closest to the actual target based on their propensity scores. I divide my sample based on $Max3_A$ terciles. Acquirers with $Max3_A$ in the top tercile are considered with strong lottery-like features, while acquirers with $Max3_A$ in the bottom tercile are considered non-lottery-like. I pool these pseudo M&A pairs with real M&A pairs together and run logit regressions, where the dependent variable equals one for actual M&A pairs, and zero otherwise. The independent variables of interests are $Combined\_Max3$, $CoMax3$, and $Combined\_Max3 \times CoMax3$. I control the same set of firm characteristics as before. Detailed descriptions of all independent variables can be found in Appendix.

Column 1 reports regression results based on the subsample of non-lottery-like acquirers (low $Max3_A$). In this subsample, none of the independent variables of interests have significant effects on the likelihood of a M&A deal. On the contrary, Column 2 shows that when acquirers have strong lottery-like features (high $Max3_A$), the estimate on $Combined\_Max3 \times CoMax3$ is 0.288 (z-statistic = 2.48). This indicates that increasing

$Combined\_Max3 \times CoMax3$ by one-standard deviation makes the two firms 29.2% more likely to announce an M&A deal relative to the unconditional likelihood.[14]

I can conduct similar analysis by matching each target with ten pseudo acquirers that are not involved in the M&A deal with this target. Pseudo acquirers are determined through propensity score matching with reference to the same set of acquirer characteristics and relative size to the target as outlined in the Section 3.1. These pseudo acquirers are the closest to the actual acquirer based on their propensity scores. I divide my sample based on $Max3_T$ terciles. Targets with $Max3_T$ in the top tercile are considered with strong lottery-like features, while targets with $Max3_T$ in the bottom tercile are considered non-lottery-like. I pool these pseudo M&A pairs with real M&A pairs together and run the same logit regressions and report the results in Columns 3 and 4 of Panel B Table 7.

Column 3 reports regression results based on the subsample of non-lottery-like targets (low $Max3_T$). Similar to Column 1, in this subsample, none of the independent variables of interests have significant effects on the likelihood of a M&A deal. On the contrary, Column 4 shows that when targets have strong lottery-like features (high $Max3_T$), the estimate on $Combined\_Max3 \times CoMax3$ is 0.183 (z-statistic = 2.38). This indicates that increasing $Combined\_Max3 \times CoMax3$ by one-standard deviation makes the two firms 20.8% more likely to announce an M&A deal relative to the unconditional likelihood.

[14] This unconditional likelihood is $1/(10+1) = 0.091$ for the first four columns.

As a final exercise, I allow both pseudo acquires and pseudo targets for each real M&A deal. This method provides me a total of 121 stock pairs (11×11) from each deal. I pool these pseudo M&A pairs with real M&A pairs together and run the same logit regressions and report the result in Columns 5. The result suggests that lottery-likeness and $CoMax$ jointly affect the likelihood of a M&A deal. The estimate on $Combined\_Max3 \times CoMax3$ is 0.166 (z-statistic = 2.08). This indicates that increasing $Combined\_Max3 \times CoMax3$ by one-standard deviation makes the pair 22.0% more likely to announce an M&A deal relative to the unconditional likelihood.[15]

To sum up, results from Table 7 indicate that mangers are aware that the diversification of lottery-like features have a negative effect on CEF prices and M&A announcement returns, and they have taken actions to mitigate the effects. Provided everything else equal, CEF managers tend to avoid lottery-like stocks at fund inception, while acquirers (targets) with strong lottery-like features tend to select targets (acquires) with strong lottery-like features and high $CoMax$. These results provide further support for my main results from Section 4, and provide managerial implications for the effect of diversification in lottery-like features.

6 Conclusion

[15] This unconditional likelihood is $1/(11 \times 11) = 0.008$.

In this paper, I extend the model of Barberis and Huang (2008) and consider multiple lottery-like stocks. These lottery-like stocks can provide extreme positive payoffs with a small probability, but they may or may not produce extreme payoffs at the same time. I solve and compare asset prices in two economies. In the first economy, investors can trade these lottery-like stocks freely. In the second economy, investors can only trade a portfolio consisting of these lottery-like stocks. I find that the portfolio price in the second economy is lower than the prices of these lottery-like stocks in the first economy. More importantly, this discount depends on how likely these lottery-like stocks produce extreme payoffs together. Specifically, when the stocks are more likely to produce extreme payoffs together, the portfolio pricing discount is smaller.

I utilize closed-end funds (CEF), mergers and acquisitions (M&A), and conglomerates to test this prediction and find consistent results from all three settings. Firstly, in all three settings, the lottery-like feature indeed gets diversified away when stocks are combined into the "portfolio". Secondly, the diversification in lottery-like features can help explain the CEF discount, the combined announcement-day return of a M&A deal, and conglomerate discount. Finally, when stocks are more likely to produce extreme payoffs together, these three discount pricing phenomena can get partially offset. My empirical evidence not only supports prospect theory from a new perspective, but also provides a novel and unifying explanation on the CEF puzzle, the M&A announcement return, and the conglomerate discount.

My paper also has managerial implications. A CEF manager may be better off by avoiding lottery-like stocks at fund inception. When evaluating potential M&A deals, a CEO should take advantage of the lottery-like feature of the firm by finding a lottery-like counterpart with high $CoMax$. Finally, it may be beneficial in terms of valuation for a conglomerate to unbundle its giant empire into smaller firms with more focused business.

References

Bali, T.G., Cakici, N. and Whitelaw, R.F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99(2), pp.427-446.

Barberis, N. and Huang, M., 2008. Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review*, 98(5), pp.2066-2100.

Barberis, N., Mukherjee, A. and Wang, B., 2016. Prospect theory and stock returns: an empirical test. *Review of Financial Studies*, 29(11), pp.3068-3107.

Berger, P.G. and Ofek, E., 1995. Diversification's effect on firm value. *Journal of Financial Economics*, 37(1), pp.39-65.

Bodurtha, J.N., Kim, D.S. and Lee, C.M., 1995. Closed-end country funds and US market sentiment. *Review of Financial Studies*, 8(3), pp.879-918.

Boyer, B., Mitton, T. and Vorkink, K., 2010. Expected idiosyncratic skewness. *Review of Financial Studies*, 23(1), pp.169-202.

Hwang, B. H., and Kim, H. H., 2017. It pays to write well. *Journal of Financial Economics*, 124(2), 373-394.

Cai, Y., and Sevilir, M., 2012. Board connections and M&A transactions. *Journal of Financial Economics*, 103(2), 327-349.

Chan, J.S., Jain, R., and Xia, Y., 2008. Market segmentation, liquidity spillover, and closed-end country fund discounts. *Journal of Financial Markets*, 11(4), pp.377-399.

Chen, N. F., Kan, R., and Miller, M. H., 1993. Are the discounts on closed-end funds a sentiment index?. *Journal of Finance*, 48(2), 795-800.

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance*, 52(3), pp.1035-1058.

Fama, E.F. and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), pp.3-56.

Green, T.C. and Hwang, B.H., 2012. Initial public offerings as lotteries: Skewness preference and first-day returns. *Management Science*, 58(2), pp.432-444.

Hund, J., Monk, D., and Tice, S., 2010. Uncertainty about average profitability and the diversification discount. *Journal of Financial Economics*, 96(3), 463-484.

Hwang, B.H., 2011. Country-specific sentiment and security prices. *Journal of Financial Economics*, 100(2), pp.382-401.

Hwang, B. H., and Kim, H. H., 2017. It pays to write well. *Journal of Financial Economics*, 124(2), 373-394.

Klibanoff, P., Lamont, O. and Wizman, T.A., 1998. Investor reaction to salient news in closed-end country funds. *Journal of Finance*, 53(2), 673-699.

Laeven, L., and Levine, R., 2007. Is there a diversification discount in financial conglomerates?. *Journal of Financial Economics*, 85(2), 331-367.

Lamont, O.A. and Polk, C., 2001. The diversification discount: Cash flows versus returns. *Journal of Finance*, 56(5), pp.1693-1721.

Lang, L.H. and Stulz, R.M., 1994. Tobin's q, corporate diversification, and firm performance. *Journal of Political Economy*, 102(6), pp.1248-1280.

Lee, C., Shleifer, A. and Thaler, R.H., 1991. Investor sentiment and the closed-end fund puzzle. *Journal of Finance*, 46(1), pp.75-109.

Masulis, R.W., Wang, C. and Xie, F., 2007. Corporate governance and acquirer returns. *Journal of Finance*, 62(4), pp.1851-1889.

Mitton, T., and Vorkink, K., 2007. Equilibrium under diversification and the preference for skewness. *Review of Financial studies*, 20(4), pp.1255-1288.

Mitton, T., and Vorkink, K., 2010. Why Do Firms with Diversification Discounts Have Higher Expected Returns? *Journal of Financial and Quantitative Analysis*,45(6), 1367-1390.

Moeller, S. B., Schlingemann, F. P., and Stulz, R. M., 2005. Wealth destruction on a massive scale? A study of acquiring-firm returns in the recent merger wave. *Journal of Finance*, 60(2), 757-782.

Morck, R., Shleifer, A., and Vishny, R. W., 1990. Do managerial objectives drive bad acquisitions?. *Journal of Finance*, 45(1), 31-48.

Pontiff, J., 1996. Costly arbitrage: Evidence from closed-end funds. *Quarterly Journal of Economics*, 111(4), 1135-1151.

Servaes, H., 1996. The value of diversification during the conglomerate merger wave. *Journal of Finance*, 51(4), 1201-1225.

Tversky, A. and Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4), pp.297-323.

Wu, Y., Wermers, R., and Zechner, J., 2016. Managerial rents vs. shareholder value in delegated portfolio management: The case of closed-end funds. *Review of Financial Studies*, 29(12), 3428-3470.

Appendix. Variable Definitions

A1. Closed-end Funds

Disagreement: The portfolio-weighted average price-scaled earnings forecast dispersion of the top-10 stocks held by the CEF.

Inverse Price: The inverse of the CEF's market price.

Dividend Yield: The sum of the dividends paid by the CEF over the past one year, divided by the CEF's market price.

Liquidity Ratio: The CEF's one-month turnover, divided by the portfolio-weighted average one-month turnover of the stocks held by the CEF. If the stock is listed on NASDAQ, I divide the number of shares traded by two.

Expense Ratio: The expense ratio of the CEF.

Excess Skewness: The difference between the return skewness of the CEF and the portfolio-weighted average return skewness of the stocks held by the CEF. Return skewness is calculated as $s = (1/22) \times \sum_t (r_t - \mu)^3 / \sigma^3$, where s is calculated using daily returns over a one-month window, μ is the mean return, and σ is the standard deviation of returns.

Excess Idiosyncratic Volatility: The difference between the idiosyncratic volatility of the CEF and the portfolio-weighted average idiosyncratic volatility of the stocks held by the CEF.

Idiosyncratic volatility is estimated based on residuals from Fama-French 3-factor model over a one-month window using daily returns.

A2. Mergers and Acquisitions

Disagreement: The average price-scaled earnings forecast dispersion across the acquirer and the target, weighted by the acquirer's and target's market capitalization in the month prior to the announcement.

Acquirer (Target) Market Capitalization: The acquirer's (target's) market capitalization in the month prior to the announcement.

Acquirer (Target) Market-to-Book Ratio: The acquirer's (target's) market-to-book ratio.

Acquirer (Target) ROA: The acquirer's (target's) earnings before interest and tax over total assets.

Acquirer (Target) Leverage: The acquirer's (target's) long-term debt over total assets.

Acquirer (Target) Operating Cash Flow: The acquirer's (target's) operating cash flows over total assets.

Relative Size: The market capitalization of the acquirer over the sum of market capitalization from the acquirer and the target.

Tender Offer: A dummy variable that equals one if a tender offer is made, and zero otherwise.

Hostile Offer: A dummy variable that equals one if the takeover is considered hostile, and zero otherwise.

Competing Offer: A dummy variable that equals one if there are multiple offers made by various companies, and zero otherwise.

Cash Only: A dummy variable that equals one if the acquirer only uses cash to purchase the target, and zero otherwise.

Stock Only: A dummy variable that equals one if the acquirer only uses stocks to purchase the target, and zero otherwise.

Same Industry: A dummy variable that equals one if the acquirer and target companies have the same two-digit SIC code, and zero otherwise.

Combined Skewness: The average return skewness across the acquirer and the target, weighted by the acquirer's and target's market capitalization in the month prior to the announcement. Return skewness is calculated as $s = (1/12) \times \sum_t (r_t - \mu)^3 / \sigma^3$, where s is calculated using monthly returns over a one-year window, μ is the mean return, and σ is the standard deviation of returns.

Combined Idiosyncratic Volatility: The average idiosyncratic volatility across the acquirer and the target, weighted by the acquirer's and target's market capitalization in the month prior to the announcement. Idiosyncratic volatility is estimated based on residuals from the Fama-French 3-factor model over a one-year window using monthly returns.

A3. Conglomerates

Disagreement: For each of the conglomerate's underlying segments, I calculate the average price-scaled earnings forecast dispersion across single-segment firms in that segment. Disagreement is the sales-weighted average of the conglomerate's underlying segment dispersions.

Total Assets: The conglomerate's total assets.

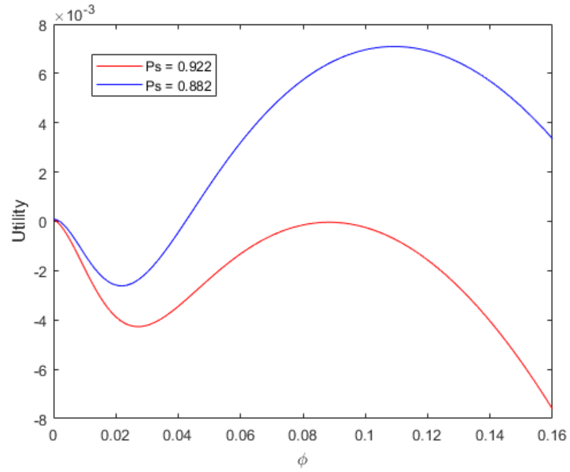
Leverage: The conglomerate's long-term debt over total assets.

Profitability: The conglomerate's earnings before interest and tax over net revenue.

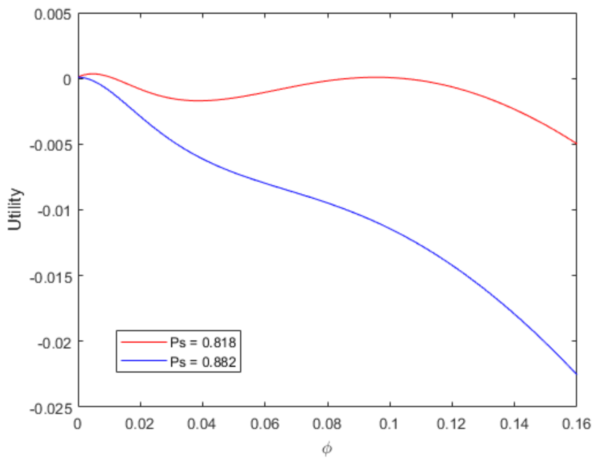
Investment Ratio: The conglomerate's capital expenditure over net revenue.

Excess Skewness: The difference between the return skewness of the conglomerate and its imputed return skewness. Return skewness is calculated as $s = (1/12) \times \sum_t (r_t - \mu)^3 / \sigma^3$, where s is calculated using monthly returns over a one-year window, μ is the mean return, and σ is the standard deviation of returns. For each of the conglomerate's underlying segments, I compute the average skewness across single-segment firms in that segment. The imputed return skewness is the sales-weighted average segment skewness.

Excess Idiosyncratic Volatility Rank: The difference between the idiosyncratic volatility of the conglomerate and its imputed idiosyncratic volatility. Idiosyncratic volatility is estimated based on residuals from the Fama-French 3-factor model over a one-year window using monthly returns. For each of the conglomerate's underlying segments, I compute the average idiosyncratic volatility across single-segment firms in that segment. The imputed idiosyncratic volatility is the sales-weighted average of those segment volatilities.



(a) $u = 0.08$



(b) $u = 0.01$

Figure 1 Heterogeneous Holdings Equilibrium and Homogeneous Holdings Equilibrium

This figure demonstrates the utility that an investor with cumulative prospect theory preferences derives from adding a position in a portfolio which equally invests in two positively skewed securities to his current holdings of a normally distributed market portfolio. The variable ϕ is the fraction of wealth allocated to the portfolio relative to the fraction of wealth allocated to the market portfolio. The variable u is the probability that both skewed securities pay out "jackpots" at the same time. In Figure 1a, $u = 0.08$, while in Figure 1b, $u = 0.01$. The price of the portfolio is denoted as p_s. Both figures use the following parameters: $(\alpha, \beta, \gamma, \delta, \lambda) = (0.88, 0.88, 0.65, 0.65, 2.25)$ and $(\sigma_m, r_f, J, v) = (0.15, 1.02, 10, 0.09)$. In both figures, the red line is based on the price of the portfolio from a heterogenous holdings equilibrium, and the blue line is based on the price from a homogenous holdings equilibrium.

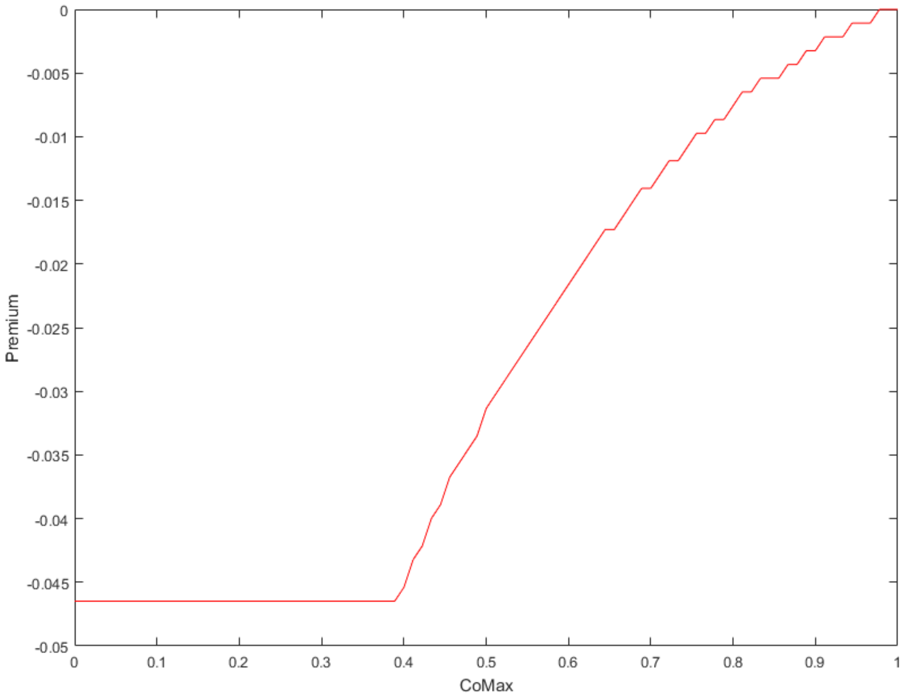
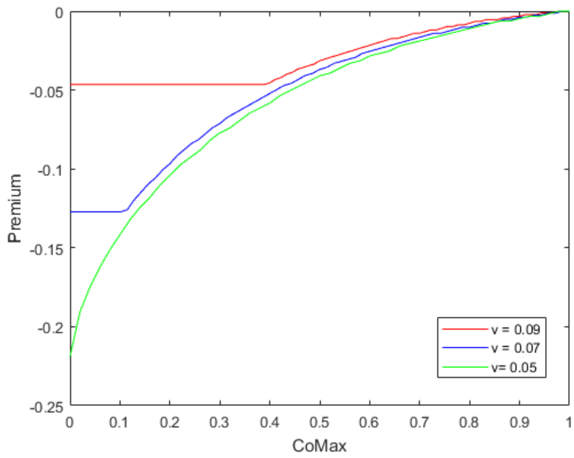
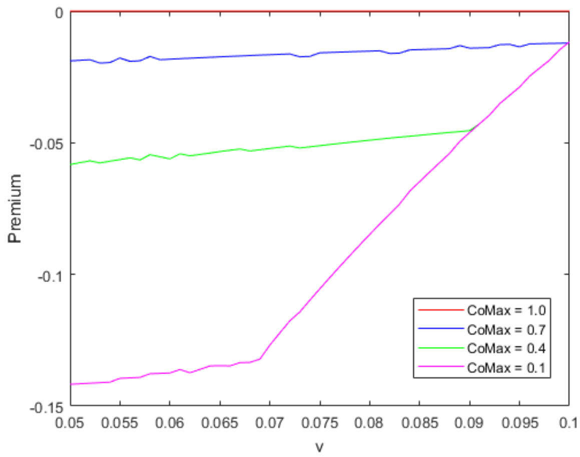


Figure 2 Portfolio Discount and $CoMax$

This figure plots the price discount of a portfolio which equally invests in two skewed securities as a function of $CoMax$. $CoMax = u/v$, where v is the probability that each skewed security pays out "jackpots" individually, and u is the probability that both skewed securities pay out "jackpots" at the same time. I use the following parameters to search the equilibrium prices for the portfolio: $(\alpha, \beta, \gamma, \delta, \lambda) = (0.88, 0.88, 0.65, 0.65, 2.25)$ and $(\sigma_m, r_f, J, v) = (0.15, 1.02, 10, 0.09)$. For each value of $CoMax$, I search for a heterogeneous holdings equilibrium first, and if it does not exist, a homogenous holdings equilibrium.



(a)



(b)

Figure 3 v, $CoMax$ and Portfolio Discount

This figure plots the price discount of a portfolio which equally invests in two skewed securities as a function of (a) $CoMax$, the tendency that both skewed securities pay off "jackpots" at the same time; and (b) v, the degree of skewness for each of the skewed securities. I use the following parameters to search the equilibrium prices for the portfolio: $(\alpha, \beta, \gamma, \delta, \lambda) = (0.88, 0.88, 0.65, 0.65, 2.25)$ and $(\sigma_m, r_f, J) = (0.15, 1.02, 10)$. For each $CoMax$ and v, I search for a heterogeneous holdings equilibrium first, and if it does not exist, a homogenous holdings equilibrium.

Table1 Descriptive Statistics

This table presents descriptive statistics for CEFs (Panel A), M&A deals (Panel B), and conglomerates (Panel C). In Panel A, CEF Discount is defined as the difference between the price of the CEF and the its NAV, divided by NAV. I use the average top 5 daily returns within a month (*Max5*) to proxy for lottery-like feature for the CEF and its holdings. I denote *CEF_Max5* as the *Max5* for a CEF and *Holding_Max5* as the average *Max5* from a CEF's holdings, weighted by holding percentage. *Ex_Max5* is the difference between *CEF_Max5* and *Holding_Max5*. For each possible stock pairs among the top ten holdings, *CoMax5* is the percentage of top 5 daily returns that are recorded in the same day, and *Pair_Max5* is the average *Max5* of the stock pair, weighted by holding percentage. *Pair_Max5*, *CoMax5*, and *Pair_Max5*×*CoMax5* are then taken weighted average across all stock pairs (I keep the same notations). Note that after *Pair_Max5* is taken weighted average across all stock pairs, it equals *Holding_Max5*. In Panel B, *Combined_CAR [-1,+1]*, i.e., the combined announcement return, is defined as the average cumulative abnormal return over days [-1,+1] across the acquirer and the target, weighted by their market capitalization in the month prior to the announcement, where *t*=0 is the announcement day, or the ensuing trading day if the deal is announced when the market is closed. The degree of lottery likeness of the acquirer (target) is proxied by the average of the acquirer's (target's) top-3 monthly returns within the past year before the announcement (denoted as $Max3_A$ and $Max3_T$). *Combined_Max3* is the average of $Max3_A$ and $Max3_T$, weighted by their respective market capitalizations in the month prior to the announcement. *CoMax3* is the percentage of the top-3 monthly returns that are recorded in the same month. In Panel C, the conglomerate discount is defined as the difference between a conglomerate's market-to-book ratio and its *Imputed_MEBE*, scaled by *Imputed_MEBE*, where *Imputed_MEBE* is defined as the average *Seg_MEBE* across a conglomerate's segments weighted by this conglomerate's net sales from each segment, and *Seg_MEBE* is defined as the sales-weighted average market-to-book values across single-segment firms within each segment. I proxy lottery-like feature for a firm by the average top-3 monthly returns within the fiscal year (*Max3*). *Ex_Max3* is defined as the difference between a conglomerate's *Max3* (*Cong_Max3*) and its *Imputed_Max3*, where *Imputed_Max3* is the average *Seg_Max3* across a conglomerate's segments, weighted by this conglomerate's net sales from each segment, and *Seg_Max3* is the sales-weighted average *Max3* across five single-segment firms chosen similar to the conglomerate's operation in that segment based on SIC code and sales. *CoMax3* is the percentage of top-3 monthly returns that are recorded in the same month for every possible stock pairs constructed from any two different underlying segments, and *Pair_Max3* is the average *Max3* from these two stocks. *Pair_Max3*, *CoMax3*, and *Pair_Max3*×*CoMax3* are then taken weighted average across all stock pairs and segment pairs (I keep the same notations). The definitions of all control variables are described in the appendix.

Panel A: Closed-end Funds						
Variables	**N**	**Mean**	**StdDev**	**p25**	**p50**	**p75**
CEF Discount	2330	-0.047	0.143	-0.124	-0.090	-0.025
Ex_Max5	2330	-0.006	0.007	-0.009	-0.006	-0.003
Holding_Max5	2330	0.020	0.010	0.014	0.017	0.022
CEF_Max5	2330	0.014	0.010	0.008	0.011	0.015
CoMax5	2330	0.445	0.102	0.372	0.436	0.512
Pair_Max5×CoMax5	2330	0.063	0.129	0.026	0.039	0.062
Disagreement	2330	0.001	0.001	0.001	0.001	0.001
Inverse Price	2330	0.094	0.068	0.055	0.075	0.107
Dividend Yield	2330	0.083	0.048	0.061	0.083	0.100
Expense Ratio	2330	0.013	0.007	0.010	0.012	0.014
Liquidity	2330	0.460	0.384	0.244	0.380	0.576
Ex_Tskew	2330	-0.405	0.753	-0.734	-0.313	0.015
Ex_Ivol	2330	-0.004	0.006	-0.007	-0.004	-0.002

Panel B: Mergers and Acquisitions						
Variables	**N**	**Mean**	**StdDev**	**p25**	**p50**	**p75**
Combined_CAR [-1,+1]	1145	0.016	0.070	-0.017	0.010	0.047
Combined_Max3	1145	0.154	0.099	0.091	0.129	0.186
CoMax3	1145	0.380	0.256	0.333	0.333	0.667
Combined_Max3×CoMax3	1145	0.062	0.068	0.023	0.046	0.081
Disagreement	1145	0.002	0.007	0.000	0.001	0.002
Acq_MktCap ($M)	1145	22543	49701	1378	4509	17441
Acq_MEBE	1145	4.278	6.342	1.818	2.873	4.923
Acq_ROA	1145	0.105	0.096	0.053	0.103	0.157
Acq_Leverage	1145	0.538	0.210	0.378	0.545	0.672
Acq_OCF	1145	0.101	0.091	0.048	0.105	0.153
Tgt_MktCap ($M)	1145	1899	5755	173	464	1425
Tgt_MEBE	1145	3.972	17.238	1.460	2.255	3.539
Tgt_ROA	1145	0.047	0.160	0.016	0.070	0.122

(*Continued*)

(*Continued*)

Variables	**N**	**Mean**	**StdDev**	**p25**	**p50**	**p75**
Tgt_Leverage	1145	0.484	0.245	0.271	0.483	0.667
Tgt_OCF	1145	0.057	0.138	0.017	0.073	0.126
Relative Size	1145	0.831	0.160	0.722	0.890	0.962
Combined_Tskew	1145	0.150	0.642	-0.238	0.147	0.549
Combined_Ivol	1145	0.076	0.048	0.045	0.065	0.095

Panel C: Conglomerates

Variables	**N**	**Mean**	**StdDev**	**p25**	**p50**	**p75**
Conglomerate Discount	15907	-0.130	0.981	-0.583	-0.292	0.171
Ex_Max3	15907	-0.014	0.105	-0.044	-0.005	0.021
Imputed_Max3	15907	0.157	0.111	0.092	0.129	0.187
Cong_Max3	15907	0.143	0.053	0.109	0.133	0.166
CoMax3	15907	0.329	0.087	0.270	0.320	0.380
Pair_Max3×CoMax3	15907	0.027	0.014	0.017	0.024	0.032
Disagreement	15907	0.050	0.052	0.015	0.032	0.066
Total Asset ($M)	15907	3507	8402	89	342	1632
Leverage	15907	0.201	0.156	0.071	0.183	0.299
Profitability	15907	0.072	0.096	0.032	0.072	0.116
Investment Ratio	15907	0.076	0.104	0.024	0.044	0.080
Ex_Tskew	15907	-0.077	0.869	-0.610	0.050	0.489
Ex_Ivol	15907	-0.011	0.056	-0.030	0.000	0.020

Table 2 Compare Lottery-like Features

This table compares lottery-like feature proxies for CEFs (Panel A), M&A (Panel B), and conglomerates (Panel C). In Panel A, I use the average top 5 daily returns within a month (*Max5*) to proxy for lottery-like feature for the CEF and its holdings. I denote *CEF_Max5* as the *Max5* for a CEF and *Holding_Max5* as the average *Max5* from a CEF's holdings, weighted by holding percentage. In Panel B, the degree of lottery likeness of the acquirer (target) is proxied by the average of the acquirer's (target's) top-3 monthly returns within the past year before the announcement (denoted as $Max3_A$ and $Max3_T$). *Combined_Max3* is the average of $Max3_A$ and $Max3_T$, weighted by their respective market capitalizations in the month prior to the announcement. In Panel C, I proxy lottery-like feature for conglomerates and single-segment firms by the average top-3 monthly returns within the fiscal year (*Max3*). *T*-statistics are provided in the brackets.

Panel A: CEFs					
	Mean	**Std Dev**	**25th Pctl**	**50th Pctl**	**75th Pctl**
Distribution of Holding's *Max5*	0.022	0.016	0.013	0.018	0.030
Distribution of CEF's *Max5*	0.014	0.010	0.008	0.011	0.015
CEF's *Max5* – Holding's *Max5*	-0.009				
	(-34.44)				
Panel B: M&A					
	Mean	**Std Dev**	**25th Pctl**	**50th Pctl**	**75th Pctl**
Distribution of $Max3_T$	0.193	0.132	0.114	0.158	0.235
Distribution of $Max3_A$	0.151	0.105	0.086	0.126	0.185
Distribution of *Combined_Max3*	0.154	0.099	0.091	0.129	0.186
$Max3_T$ – *Combined_Max3*	0.039				
	(12.34)				
$Max3_T - Max3_A$	0.042				
	(11.63)				
Panel C: Conglomerates					
	Mean	**Std Dev**	**25th Pctl**	**50th Pctl**	**75th Pctl**
Distribution of Single-Segment Firm's *Max3*	0.162	0.103	0.106	0.140	0.198
Distribution of Conglomerate Firm's *Max3*	0.143	0.053	0.109	0.133	0.166
Conglomerate's *Max3* – Single-Segment's *Max3*	-0.019				
	(-32.08)				

Table 3 Closed-end Fund Discounts

This table reports coefficient estimates from regressions of CEF discounts on measures of the lottery-like features. The dependent variable is the CEF discount, defined as the difference between the CEF's market price and the CEF's NAV, divided by NAV (expressed in %). I use the average top 5 daily returns within a month (*Max5*) to proxy for lottery-like feature for the CEF and its holdings. I denote *CEF_Max5* as the *Max5* for a CEF and *Holding_Max5* as the average *Max5* from a CEF's holdings, weighted by holding percentage. *Ex_Max5* is the difference between *CEF_Max5* and *Holding_Max5*. For each possible stock pairs among the top ten holdings, *CoMax5* is the percentage of top 5 daily returns that are recorded in the same day, and *Pair_Max5* is the average *Max5* of the stock pair, weighted by holding percentage. *Pair_Max5*, *CoMax5*, and *Pair_Max5*×*CoMax5* are then taken weighted average across all stock pairs (I keep the same notations). Note that after *Pair_Max5* is taken weighted average across all stock pairs, it equals *Holding_Max5*. Detailed description of all control variables can be found in the appendix. All independent variables are standardized to have a mean of zero and a standard deviation of one. I estimate fixed effect regressions with standard errors (reported in brackets) clustered along both time and fund dimensions. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: *CEF Discount*						
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Ex_Max5	4.794***	1.068**	0.990***				
	(1.416)	(0.486)	(0.352)				
Holding_Max5				-7.170***	-7.906***	-2.065**	-1.211***
				(2.537)	(2.483)	(0.944)	(0.409)
CEF_Max5				6.678***	6.256***	1.357*	1.647**
				(1.759)	(1.895)	(0.777)	(0.662)
Pair_Max5×*CoMax5*					1.170**	1.003**	0.520***
					(0.468)	(0.402)	(0.178)
CoMax5					0.073	-0.624	-0.802**
					(0.933)	(0.463)	(0.381)
Disagreement		-0.072	0.862*			-0.196	0.727
		(0.504)	(0.484)			(0.587)	(0.474)
Inve_Price[pos]		3.794**	-0.423			3.530*	-0.488
		(1.934)	(1.605)			(1.922)	(1.545)

(Continued)

(Continued)

	Dependent Variable: *CEF Discount*						
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Inv_Price[neg]		-1.338**	-3.878***			-1.435***	-3.909***
		(0.544)	(1.415)			(0.513)	(1.422)
Div_Yield[pos]		5.245***	1.275			5.580***	1.281
		(1.530)	(1.544)			(1.475)	(1.483)
Div_Yield[neg]		0.462	-0.726			0.689	-0.749
		(0.668)	(0.754)			(0.619)	(0.733)
Liquidity		0.368	-1.131**			0.503	-1.109**
		(0.539)	(0.498)			(0.529)	(0.483)
Exp_Ratio		1.130**	-0.199			1.090*	-0.242
		(0.570)	(0.567)			(0.593)	(0.586)
Ex_Tskew		-0.637	0.438			-0.683	0.449
		(0.488)	(0.549)			(0.479)	(0.554)
Ex_Ivol		1.636***	0.742**			1.554***	0.853**
		(0.424)	(0.375)			(0.402)	(0.381)
Fixed Effect	Time	Time	Fund, Time	Time	Time	Time	Fund, Time
Observations	2,330	2,330	2,330	2,330	2,330	2,330	2,330
R-squared	0.257	0.695	0.855	0.257	0.262	0.699	0.857

Table 4 Combined M&A Announcement Day Returns

This table reports coefficient estimates from regressions of combined M&A announcement day returns on lottery-like features. The dependent variable is combined cumulative abnormal return (*Combined CAR [−1,+1]*), where t=0 is the announcement day, or the ensuing trading day if the deal is announced when the market is closed, weighted by the market capitalization of both the acquirer and the target. The degree of lottery likeness of the acquirer (target) is proxied by the average of the acquirer's (target's) top-3 monthly returns within the past year before the announcement (denoted as $Max3_A$ and $Max3_T$). *Combined_Max3* is the average of $Max3_A$ and $Max3_T$, weighted by their respective market capitalizations in the month prior to the announcement. *CoMax3* is the percentage of the top-3 monthly returns that are recorded in the same month. Detailed description of all control variables can be found in the appendix. All independent variables are standardized to have a mean of zero and a standard deviation of one. I estimate time-fixed effect regressions with standard errors (reported in brackets) clustered by time. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: *Combined_CAR [−1,+1]*			
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
Combined_Max3	-0.990*	-1.280**	-1.268**	-1.729***
	(0.513)	(0.571)	(0.542)	(0.570)
CoMax3			0.323	0.256
			(0.211)	(0.207)
Combined_Max3×CoMax3			0.624***	0.744***
			(0.189)	(0.186)
Disagreement		-0.011		-0.032
		(0.340)		(0.343)
Ln(Acq_MktCap)		-0.894*		-0.902*
		(0.450)		(0.465)
Ln(Acq_MEBE)		-0.013		0.007
		(0.352)		(0.353)
Acq_ROA		0.157		0.179
		(0.509)		(0.475)
Acq_Leverage		-0.215		-0.203
		(0.327)		(0.318)
Acq_OCF		-0.284		-0.273
		(0.359)		(0.341)
Ln(Tgt_MktCap)		0.320		0.286
		(0.368)		(0.383)

(Continued)

(Continued)

VARIABLES	Dependent Variable: ***Combined_CAR [−1,+1]*** (1)	(2)	(3)	(4)
Ln(Tgt_MEBE)		-0.586**		-0.546**
		(0.246)		(0.247)
Tgt_ROA		-0.039		-0.043
		(0.476)		(0.474)
Tgt_Leverage		0.385		0.351
		(0.226)		(0.231)
Tgt_OCF		-0.011		0.004
		(0.476)		(0.474)
Relative Size		-0.987**		-0.996**
		(0.395)		(0.385)
Tender Offer		0.164		0.169
		(0.207)		(0.204)
Hostile Offer		0.389		0.373
		(0.241)		(0.233)
Competing Offer		-0.078		-0.043
		(0.202)		(0.191)
Cash Only		1.330***		1.288***
		(0.206)		(0.204)
Stock Only		-0.031		-0.071
		(0.295)		(0.294)
Same Industry		0.148		0.098
		(0.170)		(0.181)
Combined_Tskew		-0.173		-0.151
		(0.174)		(0.173)
Combined_Ivol		0.356		0.497
		(0.295)		(0.308)
Fixed Effect	Time	Time	Time	Time
Observations	1,145	1,145	1,145	1,145
R-squared	0.078	0.174	0.087	0.184

Table 5 Conglomerate Discounts

This table reports coefficient estimates from regressions of conglomerate discounts on measures of lotter-like features. The dependent variable is conglomerate discount, defined as the difference between a conglomerate's market-to-book ratio and its *Imputed_MEBE*, scaled by *Imputed_MEBE*, where *Imputed_MEBE* is defined as the average *Seg_MEBE* across a conglomerate's segments weighted by this conglomerate's net sales from each segment, and *Seg_MEBE* is defined as the sales-weighted average market-to-book values across single-segment firms within each segment. I proxy lottery-like feature for a firm by the average top-3 monthly returns within the fiscal year (*Max3*). *Ex_Max3* is defined as the difference between a conglomerate's *Max3* (*Cong_Max3*) and its *Imputed_Max3*, where *Imputed_Max3* is defined as the average *Seg_Max3* across a conglomerate's segments, weighted by this conglomerate's net sales from each segment, and *Seg_Max3* is defined as the sales-weighted average *Max3* across five single-segment firms chosen similar to the conglomerate's operation in that segment based on SIC code and sales. *CoMax3* is the percentage of top-3 monthly returns that are recorded in the same month for every possible stock pairs constructed from any two different underlying segments, and *Pair_Max3* is the average *Max3* from these two stocks. *Pair_Max3*, *CoMax3*, and *Pair_Max3×CoMax3* are then taken weighted average across all stock pairs and segment pairs (I keep the same notations). All independent variables are standardized to have a mean of zero and a standard deviation of one. I estimate time-fixed effect regressions with standard errors (reported in brackets) clustered by both firm and time. *, **, and *** denote significance at 10%, 5%, 1% level, respectively.

	Dependent Variable: *Conglomerate Discount*				
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Ex_Max3	0.100***	0.195***			
	(0.0184)	(0.0260)			
Imputed_Max3			-0.092***	-0.121***	-0.163***
			(0.021)	(0.026)	(0.028)
Cong_Max3			0.097***	0.097***	0.202***
			(0.021)	(0.020)	(0.028)
Pair_Max3×CoMax3				0.057**	0.074***
				(0.025)	(0.024)
CoMax3				-0.042*	-0.045**
				(0.023)	(0.021)

(Continued)

(Continued)

	Dependent Variable: *Conglomerate Discount*				
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Disagreement		-0.009			-0.008
		(0.018)			(0.018)
Ln(Total Asset)		-0.012			-0.018
		(0.107)			(0.108)
Ln(Total Asset)2		-0.005			-0.004
		(0.111)			(0.111)
Leverage		0.131***			0.130***
		(0.0239)			(0.024)
Profitability		0.082***			0.080***
		(0.022)			(0.022)
Investment Ratio		-0.007			-0.005
		(0.020)			(0.019)
Ex_Tskew		-0.046***			-0.046***
		(0.012)			(0.012)
Ex_Ivol		-0.120***			-0.126***
		(0.019)			(0.019)
Fixed Effect	Time	Time	Time	Time	Time
Observations	15,907	15,907	15,907	15,907	15,907
R-squared	0.013	0.042	0.014	0.015	0.043

Table 6 Replacing *CoMax* with Non-Max Correlation

This table conducts placebo tests by replacing *CoMax* with non-Max return correlation on CEFs (Panel A), M&A deals (Panel B), and conglomerates (Panel C). In Panel A, I report coefficient estimates from regressions of CEF discounts on measures of the lottery-like features. The dependent variable is the CEF discount, defined as the difference between the CEF's market price and the CEF's NAV, divided by NAV (expressed in %). I use the average top 5 daily returns within a month (*Max5*) to proxy for lottery-like feature for the CEF and its holdings. I denote *CEF_Max5* as the *Max5* for a CEF and *Holding_Max5* as the average *Max5* from a CEF's holdings, weighted by holding percentage. For each possible stock pairs among the top ten holdings, *Non-Max-Corr* is the return correlation excluding top 5 daily returns that are recorded in the same day and *Pair_Max5* is the average *Max5* of the stock pair, weighted by holding percentage. *Pair_Max5*, *Non-Max-Corr*, and *Pair_Max5×Non-Max-Corr* are then taken weighted average across all stock pairs (I keep the same notations). Note that after *Pair_Max5* is taken weighted average across all stock pairs, it equals *Holding_Max5*. All control variables are exactly the same as in Table 3. I estimate fixed effect regressions with standard errors (reported in brackets) clustered along both time and fund dimensions. In Panel B, I report coefficient estimates from regressions of combined M&A announcement day returns on measure of lottery-like features. The dependent variable is combined cumulative abnormal return (*Combined CAR [−1,+1]*), where t=0 is the announcement day, or the ensuing trading day if the deal is announced when the market is closed, weighted by the market capitalization of both the acquirer and the target. The degree of lottery likeness of the acquirer (target) is proxied by the average of the acquirer's (target's) top-3 monthly returns within the past year before the announcement (denoted as $Max3_A$ and $Max3_T$). *Combined_Max3* is the average of $Max3_A$ and $Max3_T$, weighted by their respective market capitalizations in the month prior to the announcement. For each deal, *Non-Max-Corr* is the return correlation excluding top-3 monthly returns that are recorded in the same month. All control variables are exactly the same as in Table 4. I estimate time-fixed effect regressions with standard errors (reported in brackets) clustered by time. In Panel C, I report coefficient estimates from regressions of conglomerate discounts on measures of lotter-like features. The dependent variable is conglomerate discount, defined as the difference between a conglomerate's market-to-book ratio and its *Imputed_MEBE*, scaled by *Imputed_MEBE*, where *Imputed_MEBE* is defined as the average *Seg_MEBE* across a conglomerate's segments weighted by this conglomerate's net sales from each segment, and *Seg_MEBE* is defined as the sales-weighted average market-to-book values across single-segment firms within each segment. I proxy lottery-like feature for a firm by the average top-3 monthly returns within the fiscal year (*Max3*). *Imputed_Max3* is defined as the average *Seg_Max3* across a conglomerate's segments, weighted by this conglomerate's net sales from each segment, and *Seg_Max3* is defined as the sales-weighted average *Max3* across five single-segment firms chosen similar to the conglomerate's operation in that segment based on SIC code and sales. *Non-Max-Corr* is the return correlation excluding top-3 monthly returns that are recorded in the same month for every possible stock pairs constructed from any two different underlying segments, and *Pair_Max3* is the average *Max3* from these two stocks. *Pair_Max3*, *Non-Max-Corr*, and *Pair_Max3×Non-Max-Corr* are then taken weighted average across all stock pairs and segment pairs (I keep the same notations). Note that after *Pair_Max3* is taken weighted average across all stock pairs and segment pairs, it equals *Imputed_Max3*. All control variables are exactly the same as in Table 5. I estimate time-fixed effect regressions with standard errors (reported in brackets) clustered by both firm and time. Detailed description of control variables from all panels can be found in the appendix. All independent variables are standardized to have a mean of zero and a standard deviation of one. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Closed-end Funds

	Dependent Variable: *CEF Discount*		
VARIABLES	**(1)**	**(2)**	**(3)**
Holding_Max5	-7.463***	-1.767**	-1.331***
	(2.384)	(0.877)	(0.500)
CEF_Max5	6.940***	1.731***	1.614***
	(1.728)	(0.574)	(0.478)
Pair_Max5×Non_Max_Corr	0.411	0.109	0.093
	(0.492)	(0.345)	(0.129)
Non_Max_Corr	-0.225	-0.598	-0.426*
	(0.910)	(0.455)	(0.229)
Controls	No	Yes	Yes
Fixed Effect	Time	Time	Fund, Time
Observations	2,330	2,330	2,330
R-squared	0.212	0.676	0.840

Panel B: Mergers and Acquisitions

	Dependent Variable: *Combined CAR[-1,+1]*	
VARIABLES	**(1)**	**(2)**
Combined_Max3	-1.036*	-1.418**
	(0.505)	(0.522)
Non_Max_Corr	0.221	0.251
	(0.218)	(0.205)
Combined_Max3×Non_Max_Corr	0.126	0.238
	(0.255)	(0.253)
Controls	No	Yes
Fixed Effect	Time	Time
Observations	1,145	1,145
R-squared	0.079	0.176

(Continued)

(Continued)

Panel C: Conglomerates

	Dependent Variable: *Conglomerate Discount*	
VARIABLES	**(1)**	**(2)**
Imputed_Max3	-0.085***	-0.119***
	(0.021)	(0.022)
Cong_Max3	0.099***	0.200***
	(0.020)	(0.028)
Pair_Max3×Non_Max_Corr	-0.058*	-0.032
	(0.033)	(0.030)
Non_Max_Corr	0.025	0.009
	(0.031)	(0.026)
Controls	No	Yes
Fixed Effect	Time	Time
Observations	15,907	15,907
R-squared	0.015	0.042

Table 7 Likelihood of Selection at CEF Inception and Likelihood of M&A

This table examines the effect of lottery-like features on the likelihood of selection at CEF inception (Panel A) and the likelihood of M&A (Panel B). In Panel A, I report coefficient estimates from logit regressions of CEFs' actual and potential holding stock pairs at inception on the pairs' lottery-like features. For each of the top-10 stocks at inception, I identify 10 pseudo stocks that are not selected but are very similar to the actual holding. Specifically, I apply propensity score matching based on firm size, book-to-market ratio and past twelve months' return and select the 10 pseudo stocks that are closest to the actual holding in terms of propensity scores. I end up with 45 actual top-10 stock pairs and 4,500 pseudo pairs for each fund at inception. I estimate pooled logit regressions, where the dependent variable equals one if the stock pair consists of actual top-10 holdings, and zero otherwise. I pool all actual and potential pairs together for logit regressions. The dependent variable equals one for the actual pairs, and zero otherwise. I use the average top 5 daily returns within a month (*Max5*) to proxy for lottery-like feature for stocks. For each possible stock pairs among the top ten holdings, *CoMax5* is the percentage of top 5 daily returns that are recorded in the same day, and *Pair_Max5* is the average *Max5* of the stock pair, weighted by holding percentage. Time fixed effects are included and standard errors are clustered by time (reported in parentheses). In Panel B, I report coefficient estimates from logit regressions of actual and potential M&A deals on measures of lottery-like features. In Columns (1) and (2), I search ten potential targets for each actual acquirer, based on propensity-score matching by reference to two-digit SIC code, firm characteristics, and relative size to the actual acquirer. These potential targets are similar to the actual target but are not involved in the M&A. The sample is further divided into two groups: non-lottery-like acquirers ($Max3_A$ in the bottom tercile) and lottery-like acquirers ($Max3_A$ in the top tercile). In Columns (3) and (4), I search ten potential acquirers for each actual target in each M&A, based on propensity-score matching by reference to two-digit SIC code, firm characteristics, and relative size to the actual target. These potential acquirers are similar to the actual acquirer but are not involved in the M&A. The sample is further divided into two groups: non-lottery-like targets ($Max3_T$ in the bottom tercile) and lottery-like targets ($Max3_T$ in the top tercile). In Column 5, I search both potential acquirers and potential targets based on the above requirements. In all five columns, I pool actual and pseudo acquirer-target pairs together and run logit regressions. The dependent variable equals one for the actual M&A, and zero otherwise. The degree of lottery likeness of the acquirer (target) is proxied by the average of the acquirer's (target's) top-3 monthly returns within the past year before the announcement (denoted as $Max3_A$ and $Max3_T$). *Combined_Max3* is the average of $Max3_A$ and $Max3_T$, weighted by their respective market capitalizations in the month prior to the announcement. *CoMax3* is the percentage of the top-3 monthly returns that are recorded in the same month. Time fixed effects are included and standard errors are clustered by time (reported in parentheses). All variables in both panels are standardized to have a mean of zero and a standard deviation of one. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: CEF Inceptions		
VARIABLES	(1)	(2)
Pair_Max5	-0.239***	-0.162***
	(0.035)	(0.063)
CoMax5		0.249***
		(0.065)
Pair_Max5×CoMax5		-0.120
		(0.084)
Stock Characteristics	Yes	Yes
Observations	172,710	172,710

Panel B: Likelihood of Mergers and Acquisitions					
	Pseudo Tgt Only		Pseudo Acq Only		Pseudo Acq and Pseudo Tgt
	Non-lottery-like Acq	Lottery-like Acq	Non-lottery-like Tgt	Lottery-like Tgt	
VARIABLES	(1)	(2)	(3)	(4)	(5)
Combined_Max3	-0.164	-0.147	-0.087	-0.083	-0.090
	(0.228)	(0.098)	(0.172)	(0.069)	(0.071)
CoMax3	0.140	-0.129	-0.016	-0.038	0.029
	(0.165)	(0.127)	(0.125)	(0.078)	(0.077)
Combined_Max3	0.003	0.288**	0.237	0.183**	0.166**
×CoMax3	(0.319)	(0.116)	(0.215)	(0.077)	(0.080)
Acquirer Characteristics	Yes	Yes	Yes	Yes	Yes
Target Characteristics	Yes	Yes	Yes	Yes	Yes
Relative Size	Yes	Yes	Yes	Yes	Yes
Observations	4,565	4,565	4,653	4,653	77,319